ANALYSTS' LONG-TERM GROWTH FORECASTS AND THE POST-EARNINGS-ANNOUNCEMENT DRIFT

BY

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DISSERTATION

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ABSTRACT

I examine the relation between the presence of analysts' long-term growth (LTG) forecasts and the post-earnings-announcement drift (PEAD). Using a sample of firm-quarters from 1995 to 2013, I find that the magnitude of PEAD is significantly smaller for firms with LTG forecasts. The relationship holds after controlling for a wide range of explanatory variables for PEAD returns or for the presence of LTG forecasts. I further investigate three non-exclusive hypotheses to explain this relationship. First, LTG forecasts may convey incremental value-relevant information that facilitates investors' processing of short-term earnings information. Second, the presence of LTG forecasts may indicate superiority in analysts' short-term forecast ability and identify firms with more efficient short-term forecasts. Third, the presence of LTG forecasts may be associated with cross-sectional differences in the persistence of earnings surprises. I find that none of these explanations fully accounts for the negative relationship between the presence of LTG forecasts and PEAD returns. Instead, the relationship may be a result of the presence of LTG forecasts capturing some unobservable firm characteristics beyond those identified in prior studies. Overall, this study contributes to the PEAD literature by identifying a novel analyst-based predictor of the cross-sectional variation in PEAD returns. The findings also advance our understanding of LTG forecasts by (1) identifying several previously undocumented determinants of the presence of LTG forecasts such as earnings volatility, R&D intensity, and trading volume, and (2) documenting a positive association between the presence of LTG forecasts and the persistence in earnings surprises.

To my parents

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CHAPTER 1: INTRODUCTION

Post-earnings-announcement drift (PEAD) is the tendency for stock prices to drift in the direction of earnings surprises in the months following quarterly earnings announcements (Ball and Brown, 1968; Bernard and Thomas, 1989, 1990). The phenomenon was first documented by Ball and Brown (1968), and is one of the most compelling challenges to the efficient market hypothesis (Fama, 1998; Hung, Li and Wang, 2014). Numerous studies have proposed explanations for PEAD (Bernard and Thomas, 1990; Hirshleifer, Lim and Teoh, 2009; Chordia and Shivakumar, 2005; Barberis, Shleifer and Vishny, 1998; Kovacs, 2015), and some studies also document variables that predict cross-sectional variations in PEAD returns (Rangan and Sloan, 1998; Narayanamoorthy, 2006; Bartov, Radhakrishnan and Krinsky, 2000). For example, Cao and Narayanamoorthy (2011) show that earnings volatility negatively predicts cross-sectional variations in the persistence of standardized unexpected earnings (SUE), as well as negatively explaining the PEAD returns. This corroborates the explanation that PEAD is due to investors' failure to fully comprehend the time-series properties of quarterly earnings. Dellavigna and Pollet (2009) document that the PEAD returns are stronger when earnings announcements occur on Fridays, in line with the explanation that PEAD is due to investor inattention. Bhushan (1994) finds that the magnitude of PEAD is associated with share prices, supporting the explanation that the transaction costs allow the existence and persistence of PEAD.

Recognizing the important roles financial analysts play in the financial market, a number of studies investigate the relation between analysts' forecasts and PEAD (Abarbanell and Bernard, 1992; Zhang, 2008). These studies find that PEAD is closely related to analysts' forecasts. For example, Abarbanell and Bernard (1992) show that analysts' short-term forecasts display the same form of underreaction to earnings information as exhibited by PEAD, and they suggest that investors' fixation on inefficient analysts' forecasts may partially explain PEAD. Zhang (2008) finds that the immediate stock market response to earnings information is larger, and that the drift is smaller, for firms with responsive analysts' short-term forecast revisions. She interprets her results as suggesting that analysts' short-term forecast responsiveness facilitates market efficiency and mitigates PEAD.

In this study, I explore the relation between the presence of analysts' long-term growth (LTG) forecasts and PEAD. LTG forecasts are one of the most common voluntary activities of financial analysts. In the year 2009, for example, around two-thirds of the analyst-followed firms have LTG forecasts, and around half of the financial analysts issue LTG forecasts. Despite the widespread availability of LTG forecasts, it is not clear what roles these forecasts play in financial markets. Most prior literature describes LTG forecasts as essentially useless. Studies show that these forecasts are highly inaccurate, overly optimistic and add little predictive power to the forecasting of long-term earnings (Rajan and Servaes, 1997; Lin and McNichols, 1998; Dechow, Hutton and Sloan, 2000; Chan, Karceski and Lakonishok, 2003). Studies also find that biases in LTG forecasts are associated with market mispricing (La Porta, 1996; Dechow and Sloan, 1997; Da and Warachka, 2011). However, the fact that analysts keep issuing LTG forecasts suggests that there is demand for such forecasts. In fact, several studies show that LTG forecasts are used by investors and analysts themselves in valuing firms (Copeland, Dolgoff and Moel, 2004; Bradshaw, 2004). Furthermore, a recent study by Jung, Shane and Yang (2012) finds that stock recommendations accompanied by LTG forecasts are more value-relevant, and analysts who publish these forecasts have better career outcomes. The authors interpret these findings to suggest that LTG forecasts provide investors with valuable information about firms' long-term prospects, and that the publication of these forecasts plays an important role in promoting market price discovery.

I hypothesize in this study that the presence of LTG forecasts may associate with the cross-sectional variations in PEAD returns through three channels. First, LTG forecasts may convey value-relevant information that facilitates investors' processing of earnings information, and thus directly mitigate PEAD (*forecast informativeness hypothesis*). Specifically, LTG forecasts may convey two kinds of information that is relevant for PEAD: short-term earnings related information and industry-wide information. LTG forecasts are forecasts for firm earnings from the current year till three to five years into the future. By definition, LTG forecasts contain short-term forecasts. In addition, since analysts take a long-term perspective when making LTG forecasts, short-term transitory fluctuations in earnings are less relevant for these forecasts. As a result, these forecasts are more likely to capture the long-term persistent part of short-term earnings. This incremental information about short-term earnings may play a role in improving investors' understanding of the implications of earnings information by enabling them to understand and use analysts' short-term forecasts better. In addition, LTG forecasts may also convey industry-related information. Mean reversion of firm earnings (Fama and French, 2000; Fairfield, Ramnath and Yohn, 2009) implies that LTG forecasts must rely greatly on analysts' understanding of the industry and macroeconomic conditions both in the short-term and in the long-term [1]. Studies show that investors' underreaction to industry-wide earnings news contributes to the drifts following analyst forecast revisions (Hui and Yeung, 2013) and earnings announcements (Kovacs, 2015). LTG forecasts may alleviate such underreaction (and thus mitigate PEAD) by facilitating investors' understanding of the industry-related information.

[1] The assumption is that any long-term related information automatically includes the short-term.

Second, the presence of LTG forecasts may indicate superiority in analysts' short-term forecast ability (*analyst ability hypothesis*). Long-term forecasting is considered in practice as highly difficult (Chan, Karceski and Lakonishok, 2003; Dichev, Graham, Harvey and Rajgopal, 2013). Thus, only analysts with superior forecast ability may be able to provide LTG forecasts. In addition, due to the information asymmetry between analysts and investors, capable analysts may also intentionally use the issuance of LTG forecasts to show their forecast ability. Consequently, the presence of LTG forecasts may be informative about the efficiency of analysts' short-term forecasts. Prior studies suggest that the efficiency of analysts' short-term forecasts relate to PEAD (Zhang, 2008; Abarbanell and Bernard, 1992). Specifically, Abarbanell and Bernard (1992) suggest that investors' fixation on inefficient analysts' forecasts causes PEAD. Zhang (2008) argues that analysts' timely revisions of their short-term forecasts mitigate PEAD[2]. Thus, the presence of LTG forecasts may be associated with lower PEAD returns if it identifies firms with higher analysts' short-term forecast efficiency.

Third, the presence of LTG forecasts may associate with firms' time-series properties of earnings, or in other words, autocorrelations in SUEs (*earnings persistence hypothesis*). For example, the demand for long-term oriented information is likely high after a corporate restructure, while the persistence of earnings is likely to be low. This leads to a negative association between the presence of LTG forecasts and SUE persistence. Conversely, the persistence of earnings is likely to be low when there is high information uncertainty, while analysts are less likely to issue LTG forecasts under this situation due to increased information processing costs in a highly uncertain information environment. This leads to a positive

[2] Zhang (2008) argues that analysts' forecast efficiency has two aspects: time and magnitude. While Abarbanell and Bernard's (1992) investigation of analysts' forecast efficiency focus on the magnitude aspect, Zhang's (2008) investigation focuses on the time aspect.

association between the presence of LTG forecasts and SUE persistence. Prior studies suggest that investors' insufficient understanding of the cross-sectional differences in SUE persistence results in predictable cross-sectional variations in PEAD returns (Rangan and Sloan, 1998; Narayanamoorthy, 2006; Cao and Narayanamoorthy, 2011). Along this line of reasoning, to the extent that the presence of LTG forecasts is associated with lower SUE persistence, and investors fail to understand this relation, we would observe lower PEAD returns for firms with LTG forecasts.

My empirical analyses start with an examination of the association between the ex-ante presence of LTG forecasts and PEAD returns. Using a sample of firm-quarters during 1995-2013 with analysts' short-term forecasts, I find that the magnitude of PEAD is significantly smaller for firms that also have LTG forecasts. While the average spread in abnormal returns between top and bottom SUE deciles is 6.7% per quarter for firms without LTG forecasts, it is 2.2% per quarter for firms with LTG forecasts. This return difference remains statistically significant after controlling for a wide range of explanatory variables used in prior research to explain the cross-sectional variations in PEAD returns.

I further assess each of the three non-mutually exclusive hypotheses about the sources of this return predictability. First, if the relationship between the presence of LTG forecasts and PEAD returns is due to LTG forecasts conveying value-relevant information which facilitates market efficiency (*forecast informativeness hypothesis*), we would expect that the timing of LTG forecast revisions matters. In other words, even if a firm has LTG forecasts, if analysts do not revise these forecasts in a timely manner after earnings announcements, we would not expect that these forecasts play a role in mitigating PEAD. I find that for a sample of firms with responsive analysts' short-term forecast revisions, the responsiveness of LTG forecast revisions does not have any effect on PEAD returns beyond the effect of firm size. This is inconsistent with the forecast informativeness hypothesis as an explanation for the negative relationship between the presence of LTG forecasts and PEAD returns.

Second, if the relationship between the presence of LTG forecasts and PEAD returns is due to the presence of LTG forecasts indicating superior analysts' short-term forecast ability (*analyst ability hypothesis*), we would expect that there is a positive association between the presence of LTG forecasts and analysts' short-term forecast efficiency. With respect to this prediction, I find mixed evidence. Results show that the presence of LTG forecasts is associated with more responsive analysts' short-term forecast revisions, but it is not associated with the correlation between analysts' short-term forecast errors and SUE[3]. If the relationship between the presence of LTG forecasts and PEAD returns is solely driven by its predictive power for future analysts' short-term forecast responsiveness, the relationship should not be significant after this responsiveness is controlled for. However, this is not what I find. The effect of LTG forecasts on PEAD returns remains statistically significant, and only goes slightly from -0.038 to -0.033, after controlling for the responsiveness of analysts' short-term forecasts. Thus, I interpret the results as inconsistent with the analyst ability hypothesis as an explanation for the negative relationship between the presence of LTG forecasts and PEAD returns.

Third, if the relationship between the presence of LTG forecasts and PEAD returns is due to the association between the presence of LTG forecasts and the time-series properties of earnings (*earnings persistence hypothesis*), we would expect that there is a negative association between the presence of LTG forecasts and SUE persistence. However, I find that SUE

[3] Analysts' short-term forecast efficiency is measured from two aspects: time and magnitude. Following Zhang (2008), I use the responsiveness in analysts' short-term forecast revisions to capture the time aspect of analysts' short-term forecast efficiency. Following Abarbanell and Bernard (1992), I use the correlation between analysts' short-term forecast errors and SUE to capture the magnitude aspect of analysts' short-term forecast efficiency.

persistence is not lower, but higher, for firms with LTG forecasts. Further analysis using Mishkin (1983) tests reinforces this finding. The results suggest that the negative relationship between the presence of LTG forecasts and PEAD returns is not driven by investors' underestimation of the effect of LTG forecasts on SUE persistence (i.e., earnings persistence hypothesis), but is likely a result of higher price efficiency associated with firms with LTG forecasts.

Lastly, I control for a basket of firm-level determinants of LTG forecasts which may have confounding effects on the presence of LTG forecasts and PEAD returns. Some of these firm-level determinants of LTG forecasts were not examined in prior studies. Specifically, I find that firm-quarters are more likely to have LTG forecasts when earnings volatility and R&D intensity are lower, when trading volume is higher, when the firm has recently been through a restructuring, or when the earnings announcements are for the fourth fiscal quarter. Nevertheless, controlling for these LTG forecast determinants does not change the results. Overall, my findings suggest that the negative relationship between the presence of LTG forecasts and PEAD returns is not due to any of the three explanations hypothesized, and thus I conjecture that it may be a result of the presence of LTG forecasts capturing some unobservable firm characteristics beyond those identified in prior studies.

This study makes several important contributions. First, it extends the literature on PEAD. The extant studies have long been interested in identifying variables that predict the cross-sectional variations in PEAD returns (Rangan and Sloan, 1998; Narayanamoorthy, 2006; Bartov, Radhakrishnan and Krinsky, 2000). While several studies document a close relation between analysts' forecasts and PEAD (Abarbanell and Bernard, 1992; Zhang, 2008), this is the first one that investigates the relationship between the presence of LTG forecasts and PEAD. It contributes not only by identifying an analyst-based novel predictor of the cross-sectional variations in PEAD returns, but also by exploring various hypotheses that provide explanations for the relationship.

Second, this study also extends studies on LTG forecasts. Although much time and effort is spent issuing LTG forecasts, their value has been controversial (Chan, Karceski and Lakonishok, 2003; Dechow and Sloan, 1997; Copeland, Dolgoff and Moel, 2004; Jung, Shane and Yang, 2012). This study explores the uses of LTG forecasts from two new perspectives: (1) whether these forecasts play a direct role in facilitating market efficiency, and (2) whether the presence of these forecasts captures information about analysts' ability and firms' fundamental earnings process. The findings from this study advance our understanding of LTG forecasts by (1) ruling out the direct role of these forecasts in mitigating PEAD, and (2) showing that the presence of LTG forecasts is an indicator of analysts' short-term forecast responsiveness, as well as SUE persistence. The findings also add to the literature on LTG forecasts by identifying the following previously undocumented determinants of the presence of LTG forecasts: earnings volatility, R&D intensity, trading volume, restructuring and fourth quarter earnings announcements.

Finally, the findings from this study are relevant to investors. For investors who trade on the drift following earnings announcements, findings from this study may help them improve their trading strategy by taking into account the presence or absence of LTG forecasts. Specifically, this study suggests that PEAD strategy earns higher returns for firms without LTG forecasts (6.7% per quarter) than for firms with LTG forecasts (2.2% per quarter). Focusing on firms without LTG forecasts increases the PEAD strategy returns by more than half from approximately 4.1% to 6.7% per quarter.

The rest of the paper proceeds as follows. Chapter 2 reviews related literature. Chapter 3 develops the hypotheses. Chapter 4 describes the data and methodology. Chapter 5 reports the basic characteristics of LTG forecasts. Chapter 6 and 7 present the main empirical results. Chapter 8 concludes.

CHAPTER 2: RELATED LITERATURE

This study is related to three main strands of prior literature. First, it is related to an extensive body of work on the PEAD. Second, it relates to the studies on the relationship between analysts' short-term forecasts and PEAD. Third, it is related to the emerging literature on LTG forecasts.

2.1 Post-earnings-announcement drift

A market is defined as informationally efficient if prices fully reflect all available information on a timely basis (Fama, 1969). While the informational efficiency of stock markets is crucial for a modern capitalist economy to achieve its goal of allocation efficiency (Fama, 1969; Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Kothari, 2001), mounting empirical evidence shows that stock prices adjust to information with delays and errors, or in other words, that stock markets are not fully efficient (Shleifer, 2000; Lee, 2001; Schwert, 2003; Subrahamanyam, 2010). Among the most compelling evidence is the presence and the persistence of the PEAD.

PEAD is the tendency for stock prices to drift in the direction of earnings surprises in the months following quarterly earnings announcements (Ball and Brown, 1968; Bernard and Thomas, 1989, 1990; Bartov, Radhakrishnan and Krinsky, 2000; Ng, Rusticus and Verdi, 2008). The extant literature has proposed two major explanations for the phenomenon: risk (e.g., Garfinkel and Sokobin, 2006; Sadka, 2006) and mispricing (e.g., Bernard and Thomas, 1989, 1990). The mispricing explanations for PEAD generally come from several perspectives.

First, an extensive line of studies since Bernard and Thomas (1989, 1990) attributes PEAD to investors' insufficient understanding of the time-series properties of quarterly earnings

(Abarbanell and Bernard, 1992; Ball and Bartov, 1996; Maines and Hand, 1996; Soffer and Lys, 1999; Brown and Han, 2000). Specifically, Bernard and Thomas (1990) show that, following an earnings announcement, returns around subsequent quarters' earnings announcements exhibit the same autocorrelation patterns as those documented for seasonally differenced earnings in Foster (1977). This is consistent with investors' inability to fully comprehend the autocorrelation structures in seasonally differenced earnings, and with stock prices only adjusting gradually to a component of unexpected earnings, which is predictable from past earnings. The major predictions that come out of this line of explanation is that the magnitude of the drift is either associated with the time-series properties of earnings, or investors' understanding of them. Empirical results generally support this prediction. On the one hand, studies show that factors associated with the time-series properties of earnings (e.g., loss, fourth quarter earnings announcement, earnings volatility) are associated with the magnitude of the drift (Rangan and Sloan, 1998; Narayanamoorthy, 2006; Cao and Narayanamoorthy, 2011). On the other hand, studies document that proxies for investor sophistication, such as institutional ownership, significantly explain the magnitude of the drift (Bartov, Radhakrishnan and Krinsky, 2000).

Second, an emerging literature links PEAD to investor inattention (Hirshleifer, Myers, Myers and Teoh, 2008; Hirshleifer, Lim and Teoh, 2009, 2011; Hung, Li and Wang, 2014; Dellavigna and Pollet, 2009; Aboody, Lehavy and Trueman, 2010). For example, Hirshleifer, Lim and Teoh (2009) document that the PEAD is stronger when a great number of same-day earnings announcements are made by other firms. Dellavigna and Pollet (2009) show that there is a higher delayed price response to earnings announcements which occur on Fridays. The major prediction that can be expected from this line of explanation is that the magnitude of PEAD is associated with investor attention.

Studies have also linked PEAD to several other behavioral biases, such as: underreaction to industry-wide information (Kovacs, 2015), failure to incorporate macro-economic information such as inflation (Chordia and Shivakumar, 2005, 2006; Basu, Markov and Shivakumar, 2010), investor sentiment (Barberis, Shleifer and Vishny, 1998; Mian and Sankaraguruswamy, 2012), overconfidence about the precision of private information and biased self-attribute (Daniel, Hirshleifer and Subrahmanyam, 1998), overconfidence in less reliable information (Liang, 2003), momentum trading (Hong and Stein, 1999), and tendency of investors to ride losses and realize gains (Frazzini, 2006). As greater information uncertainty leaves more room for behavioral biases (Hirshleifer, 2001), a common prediction following all behavioral explanations for PEAD is that the magnitude of the drift should be higher for firms with higher information uncertainty (Zhang, 2006). Francis, Lafond, Olsson and Schipper (2007) provide support for this prediction.

In addition, the mispricing explanations for PEAD inevitably raise the question of why rational investors do not arbitrage away the apparent mispricing. Thus, another line of research, which closely relates to the mispricing explanations for PEAD, is the limit-to-arbitrage (Mendenhall, 2004; Bhushan, 1994; Ng, Rusticus and Verdi, 2008; Ke and Ramalingegowda, 2005). For example, Mendenhall (2004) argues that the reason arbitrage does not eliminate the PEAD is that the required trades are risky. He finds that the magnitude of the drift is positively associated with the risk faced by arbitrageurs who hedge their positions in the mispriced stocks using various market indexes. Bhushan (1994) argues that transaction costs constrain the trading activities of professionals. Thus, even in an informationally efficient market, the drift may exist up to the magnitude of transaction costs. The author shows that the magnitude of the drift is associated with various proxies for transaction costs (e.g., share prices, annual dollar trading volume).

2.2 Analysts' forecasts and PEAD

There is abundant empirical and theoretical evidence on the association between analysts' forecasts and market efficiency in general, but there is less empirical evidence on the association between those forecasts and PEAD. As there is no reason to expect that PEAD differs from other forms of market efficiency in terms of its association with analysts' forecasts, I review here literature on the association between analysts' forecasts and market efficiency in general, as well as PEAD in particular.

Financial analysts, as important information intermediaries, collect, interpret, and disseminate information about firms. Ideally, analyst activities could have a positive impact on market efficiency for a number of reasons. First, analysts enjoy economies of scale in information processing. Instead of each investor directly searching and processing information about firms, analysts perform the same tasks at much lower costs (Levine, 2005; Fabozzi, Modigliani, Jones, 2009). Information processing cost is one of the major market frictions that impede market efficiency (Grossman and Stiglitz, 1980; Merton, 1987). Analysts alleviate such friction and allow more efficient incorporation of information into stock prices. Second, analysts are financial experts who research firm fundamentals for a living. They likely have the time, money and skills that enable them to uncover private information, or to interpret public information better than a marginal investor. Through their searching for private information, they enable more information to be incorporated into stock prices. Their interpretation of public information aids investors in information processing, and allows information to be incorporated into stock prices with greater accuracy. Third, analysts, like the business press, are important information channels. The dissemination of analysts' reports increases the information flow in the market, and enables information to be impounded into stock prices at faster speeds.

However, analysts are not perfect intermediaries. Not only may they, as human beings, suffer from the same kinds of behavioral biases as investors, but they may also face incentive issues which investors do not face (Healy and Palepu, 2001; Frankel, Kothari, Weber, 2006). For example, analysts' forecasts and recommendations have been widely accused of being inaccurate and biased due to conflicts of interest from investment banking and trading businesses (Dugar and Nathan, 1995; Lin and McNichols, 1998; Cowen, Groysberg and Healy, 2006; Bradshaw, 2011). Research also suggests that they compromise their objectivity in order to curry favor with firm management (Francis and Philbrick, 1993). These incentive issues raise questions about analysts' effectiveness as information intermediaries, or in their ability to improve market efficiency.

Given that the relation between analysts' forecasts and market efficiency is influenced by multiple forces, the net effect of these forces is an empirical issue. A large number of empirical studies focuses on the role of analysts' short-term forecasts in mitigating market inefficiency (Healy and Palepu, 2001; Frankel, Kothari, Weber, 2006). They document that analysts' short-term forecast coverage facilitates markets' incorporation of information on accruals and cash flows (Barth and Hutton, 2004), past returns (Hong, Lim and Stein, 2000), book-to-market ratios (Griffin and Lemmon, 2002) and analysts' forecast revisions (Elgers, Lo and Pfeiffer, 2001; Gleason and Lee, 2003).

Empirical evidence on the association between analysts' forecasts and PEAD focuses on two issues. First, studies show that the efficiency of analysts' short-term forecasts is associated with the magnitude of PEAD. Specifically, Zhang (2008) finds that analysts' timely short-term forecast revisions mitigate PEAD. Abarbanell and Bernard (1992) document that analysts' underreaction to earnings information partially explain the magnitude of PEAD. Second, analysts' short-term forecast coverage does not appear to play a role in mitigating PEAD (Bhushan, 1994), which contradicts results from studies of other market inefficiencies. Bhushan (1994) explains this result as (1) analysts themselves not fully understanding the time-series properties of earnings, (2) forecast errors of analysts following a firm may be highly correlated, and (3) analysts may not do better than professional arbitrageurs in understanding the implications of current earnings for future earnings.

To summarize, financial analysts are important, but imperfect, information intermediaries. On the one hand, analysts may mitigate market inefficiency by lowering information processing costs, uncovering new information, aiding investors in interpreting existing information, or facilitating information flow to investors. On the other hand, analysts may contribute to market inefficiency due to the opportunistic incentives they face and may act upon. Prior empirical evidence on the relation between analysts' forecasts and market efficiency exclusively focuses on analysts' short-term forecasts. And we know nothing about the relationship between analysts' LTG forecasts and market efficiency. This study fills this void.

2.3 Analysts' LTG forecasts

LTG forecasts are one of the most common forms of analysts' voluntary activities. Yet it has been controversial whether these analysts' forecasts are of value to the financial market. While some studies question the value of LTG forecasts, some others support their usefulness.

Evidence questioning the value of LTG forecasts comes from several perspectives. First, studies on the properties of LTG forecasts show that these forecasts are highly inaccurate (Harris, 1999) and overly optimistic (Rajan and Servaes, 1997; Dechow, Hutton and Sloan, 2000). Second, studies examining the usefulness of LTG forecasts in earnings forecasting document that these forecasts are of limited value in predicting future long-term earnings (Chan, Karceski and Lakonishok, 2003; Bradshaw, Drake, Myers and Myers, 2012). Third, research on analyst incentives show that underwriting incentives (Lin and McNichols, 1998; Dechow, Hutton and Sloan, 2000) and trading incentives (Cowen, Groysberg and Healy, 2006) significantly impact LTG forecasts[4].

In addition, a fourth line of evidence comes from investigations on the relation between LTG forecasts and future stock returns. These studies document several market irregularities (or predictable return patterns) associated with ex ante proxies for errors in LTG forecasts (La Porta, 1996; Dechow and Sloan, 1997; Da and Warachka, 2011). They interpret the results as indicating that errors in LTG forecasts mislead investors and cause market inefficiencies.

On the other hand, there is also evidence that supports the usefulness of LTG forecasts. First, during the period 1983 to 2014, 52% of the analysts had issued at least one LTG forecast, and 77% of the firms had been covered by analysts' LTG forecasts. The fact that analysts commonly issue LTG forecasts suggests that there is demand for such forecasts.

Research also shows that LTG forecasts are used by investors and analysts themselves in valuing firms. For example, Copeland, Dolgoff and Moel (2004) show that revisions of these forecasts significantly explain contemporaneous market-adjusted returns, while Bradshaw (2004) documents analysts' use of these forecasts in generating stock recommendations.

[4] More specifically, Lin and McNichols (1998) find that lead and co-underwriter LTG forecasts are more favorable than those issued by unaffiliated analysts. Dechow, Hutton and Sloan (2000) document a positive relation between the fees paid to the affiliated analysts' employers and the level of the affiliated analysts' LTG forecasts. Cowen, Groysberg and Healy (2006) show that analysts at firms that fund research through trading commissions make the most optimistic LTG forecasts.

Perhaps the most important piece of evidence is a recent study by Jung, Shane and Yang (2012) which documents that stock recommendations accompanied by LTG forecasts are more value-relevant, and analysts who publish these forecasts have better career outcomes. The authors interpret these findings to suggest that publication of LTG forecasts reflects analysts' effective effort towards uncovering value-relevant information about firms' long-term prospects.

In summary, whether LTG forecasts are of value to the financial market has been controversial. While some evidence shows that these forecasts are useless and misleading, some other evidence shows that these forecasts play an important role in the financial market. This paper introduces two new perspectives on the issue. First, this study is the first to investigate the role of LTG forecasts in facilitating market efficiency. Second, while most prior literature looks at the usefulness of the *contents* of LTG forecasts in predicting future earnings, this is the first study that examines the relation between the *presence* of LTG forecasts and future analysts' short-term forecast efficiency, as well as future SUE persistence.

CHAPTER 3: HYPOTHESIS DEVELOPMENT

3.1 The presence of LTG forecasts and PEAD returns

My first hypothesis pertains to the relation between the presence of LTG forecasts and PEAD returns. While there are some reasons to expect that the presence of LTG forecasts associates with PEAD returns, there are also reasons to expect that they do not associate.

On the one hand, the ex-ante presence of LTG forecasts may negatively associate with PEAD returns for at least three reasons. First, LTG forecasts may convey value-relevant information that facilitates investors' processing of earnings information, and thus directly mitigate PEAD (*forecast informativeness hypothesis*). Specifically, two kinds of information contained in LTG forecasts may be relevant for mitigating PEAD. The first kind of information is short-term earnings related information. LTG forecasts are forecasts for firm earnings from the current year till three to five years later. By definition, LTG forecasts contain short-term forecasts. In addition, since analysts take a long-term perspective when making LTG forecasts, short-term transitory fluctuations in earnings are less relevant for these forecasts. As a result, these forecasts are more likely to capture the long-term persistent parts of short-term earnings. This incremental information about analysts' short-term forecasts may enable investors to understand and to use analysts' short-term forecasts better. Thus, LTG forecasts may play a role in improving investors' understanding of earnings information (and thus in mitigating PEAD) by enabling better uses of analysts' short-term forecasts by investors. The second kind of information contained in LTG forecasts is industry-related information. Research shows that firm performance mean-reverts in the long-term (Fama and French, 2000; Fairfield, Ramnath and Yohn, 2009). Above-average performance attracts competition or mimics, while firms with below-average performance are incentivized to reallocate resources to better uses, or to make improvements to avoid failure or takeover. Mean reversion of firm earnings implies that LTG forecasts may convey a great amount of information about analysts' understanding of the industry and macroeconomic conditions. Studies show that investors' underreaction to industry-wide earnings news contributes to various underreaction anomalies. For example, Hui and Yeung (2003) show that the post-forecast revision drift is driven by investors' underreaction to the higher persistence of industry-wide earnings, while Kovacs (2015) suggests that underreaction to industry-related information contributes to PEAD. To the extent that investors' insufficient understanding of the industry-related information at least partially explains PEAD, and that LTG forecasts facilitate investors' understanding of the industry-related earnings news, LTG forecasts may play an active role in mitigating PEAD.

Second, the presence of LTG forecasts may indicate superiority in analysts' short-term forecast ability (*analyst ability hypothesis*). Long-term forecasting is considered in practice as highly difficult (Chan, Karceski and Lakonishok, 2003; Dichev, Graham, Harvey and Rajgopal, 2013). Thus, only analysts with superior forecast ability may be able to provide LTG forecasts. In addition, due to the information asymmetry between analysts and investors, capable analysts may intentionally use the issuance of LTG forecasts to show their superior industry knowledge, as well as exceptional ability in earnings forecasting. Consequently, the presence of LTG forecasts may be indicative about the efficiency of analysts' short-term forecasts. Prior literature suggests that the efficiency of analysts' short-term forecasts closely relates to PEAD. For example, Zhang (2008) documents that the magnitude of PEAD is smaller for firms with timely analysts' short-term forecast revisions. Abarbanell and Bernard (1992) show that analysts' underreaction to earnings information partially explains the magnitude of PEAD. To the extent that investors' fixation on inefficient analysts' forecasts explains PEAD, or that timely analysts' forecasts mitigate PEAD, the presence of LTG forecasts may relate to PEAD by ex-ante identifying firms with higher analysts' short-term forecast efficiency.

Third, the presence of LTG forecasts may associate with autocorrelations in SUEs, or SUE persistence (*earnings persistence hypothesis*). Specifically, the presence of LTG forecasts can either negatively or positively associate with SUE persistence. For example, a corporate restructure increases the demand for long-term oriented information, while decreases the persistence in SUE, resulting in a negative relationship between the presence of LTG forecasts and SUE persistence. Conversely, both the SUE persistence of a firm and its likelihood to have LTG forecasts are likely to be positively associated with its information uncertainty, resulting in a positive relationship between the presence of LTG forecasts and SUE persistence. Prior studies suggest that investors' insufficient understanding of the cross-sectional differences in SUE persistence leads to predictable cross-sectional variations in PEAD returns (Rangan and Sloan, 1998; Narayanamoorthy, 2006; Cao and Narayanamoorthy, 2011). Thus, to the extent that the presence of LTG forecasts is associated with lower SUE persistence, and investors fail to understand this relation, we would observe lower PEAD returns for firms with LTG forecasts.

On the other hand, there are also reasons to expect that the presence of LTG forecasts is not associated with PEAD returns. First, LTG forecasts may not convey short-term or industry related information if these forecasts are highly inaccurate or overly biased. Analysts face various incentive issues, and choose whether or not to undertake opportunistic actions according to the costs and benefits associated with such actions. The costs of undertaking opportunistic actions include potential reputation losses, while the benefits include increased compensation through investment banking and trading business, or better relationships with firm managers (e.g., Brown, Call, Clement and Sharp, 2015). While analysts may suffer greatly in reputation if they consistently perform poorly in short-term forecasts, forecast errors in LTG forecasts are hardly noticeable[5] and are not expected to have a great impact on analysts' reputation. Therefore, due to the low costs of issuing inaccurate or biased LTG forecasts, it may be more likely for analysts to distort these forecasts to meet their incentive needs.

Second, analysts' opportunistic incentives may not only distort the contents of LTG forecasts (as mentioned above), but also distort their decisions of whether or not to issue LTG forecasts. For example, analysts who are not able to support, through short-term forecasts, the inflated valuations they give to firms, may intentionally issue hard-to-verify LTG forecasts in order to justify their high valuations. To the extent that analysts distort the decisions of whether or not to issue LTG forecasts, the presence of LTG forecasts may have little indicative value either of analysts' ability or of firms' fundamental earnings process.

In summary, there are both reasons to expect that firm-level presence of LTG forecasts either does or does not relate to PEAD. Therefore, I test the following non-directional hypothesis about the presence of LTG forecasts and PEAD returns:

H1: There is no significant difference in the magnitude of PEAD between firms that are followed by analysts who issue LTG forecasts and firms that are followed by analysts who do not issue these forecasts.

3.2 Forecast informativeness hypothesis

[5] This is because any inaccuracy in LTG forecasts takes three to five years to become apparent. Suppose that the salience of information decreases with time, by the time the inaccuracy in LTG forecasts is apparent, this information may not be salient any more for investors.

Forecast informativeness hypothesis states that LTG forecasts convey value-relevant information that facilitates investors' processing of earnings information, and thus mitigate PEAD. One testable prediction that comes out of this hypothesis is that, if it is the information that is conveyed through LTG forecasts that facilitates market efficiency, the timing of LTG forecast revisions should matter for these forecasts to have an effect on PEAD. Specifically, as new information is conveyed through forecast revisions, only timely LTG forecast revisions after earnings announcements can potentially help mitigating PEAD, and not forecast revisions that happen long before or long after earnings announcements. Thus, to investigate whether the relationship, if any, between the presence of LTG forecasts and PEAD returns is due to LTG forecasts being informative, I test the following prediction:

H2: For a sample of firms with responsive short-term analyst forecast revisions, the magnitude of PEAD is smaller for firms that also have responsive LTG forecast revisions.

3.3 Analyst ability hypothesis

Analyst ability hypothesis states that the presence of LTG forecasts indicates higher analysts' short-term forecast efficiency; and to the extent that inefficient analysts' short-term forecasts contribute to PEAD, or that efficient analysts' short-term forecasts mitigate PEAD, the presence of LTG forecasts relates to lower PEAD by identifying firms with more efficient analysts' short-term forecasts. Following prior literature, I examine analysts' forecast efficiency from two aspects: forecast timeliness (Zhang, 2008), and the correlation between forecast errors and SUE (Abarbanell and Bernard, 1992). The testable predictions associated with this hypothesis are that, for firms with LTG forecasts, analysts' short-term forecasts should be timelier, and the correlation between analyst forecast errors and SUE should be smaller. Thus, to investigate whether the relationship, if any, between the presence of LTG forecasts and PEAD returns is due to LTG forecasts indicating superior analysts' short-term forecast ability, I test the following predictions:

H3a: Analysts' short-term forecast revisions after earnings announcements are timelier for firms with LTG forecasts.

H3b: The correlation between analysts' short-term forecast errors and earnings surprises is smaller for firms with LTG forecasts.

3.4 Earnings persistence hypothesis

Earnings persistence hypothesis states that the presence of LTG forecasts associates with SUE persistence; and to the extent that the presence of LTG forecasts indicates lower SUE persistence, and that investors fail to understand this relation, we would observe lower PEAD returns for firms with LTG forecasts. The testable predictions associated with this hypothesis are: (1) autocorrelations in SUEs are lower for firms with LTG forecasts, and (2) earnings expectations embedded in stock prices do not reflect the lower SUE persistence for firms with LTG forecasts. Thus, to investigate whether the relationship, if any, between the presence of LTG forecasts and PEAD is due to LTG forecasts capturing cross-sectional variations in SUE persistence, I test the following predictions:

H4a: The autocorrelations in SUEs are smaller for firms with LTG forecasts.

H4b: Earnings expectations embedded in stock prices do not reflect the differences in SUE persistence for firms with and without LTG forecasts.

CHAPTER 4: DATA AND METHODOLOGY

4.1 Sample selection

Data used in this study are obtained from CRSP-Compustat Merged (quarterly), CRSP (daily), I/B/E/S (summary and detail) and CDA/Spectrum databases. The sample selection procedure starts with all quarterly earnings announcements from CRSP-Compustat Merged database between 1995 and 2013. I delete observations with (i) more than one earnings announcement on the same date, (ii) earnings announcement date less than 35 days or more than 150 days after the previous earnings announcement date or (iii) earnings announcement date on/before or more than 95 days after the corresponding fiscal period-end, as these observations are potentially subject to data errors. I restrict the sample to announcements that have stock return data in CRSP and have quarterly earnings forecasts in I/B/E/S. Institutional ownership data is obtained from CDA/Spectrum. I require that every observation has non-missing data to calculate SUE. To avoid the possible influence of small illiquid stocks, I eliminate penny stocks (stocks with price lower than $1). My final sample consists of 9,166 firms and 219,098 firm-quarter observations from 1995 to 2013. Table 1 summarizes the sample selection procedure.

4.2 Variable definitions

Figure 1 shows the timeline for measurement of variables. Following prior literature (Livnat and Mendenhall, 2006; Zhang, 2008; Zhang, 2012), the drift window starts two trading days after quarter t earnings announcement date and ends one trading day after quarter t+1 earnings announcement date. The presence of LTG forecasts is measured in the month prior to the month of quarter t earnings announcements. Consistent with Zhang (2008), short- and long-term forecast responsiveness are measured within two trading days after quarter t earnings announcement, which are trading days 0 and 1.

My analyses focus on the effects of firm-level presence of LTG forecasts on PEAD returns. The main dependent variable of interest is abnormal returns during the quarter after earnings announcements. Following Zhang (2008), I use size-adjusted returns (ARQ) as proxy for abnormal returns, and define ARQ as the difference between a firm's quarterly buy-and-hold returns (calculated as the compounded raw returns, starting from two days after quarter t earnings announcement through one day after quarter t+1 earnings announcement) and the same period returns for the size decile for which the firm belongs (where size deciles are determined by the total market capitalizations on the earnings announcement date).

The main independent variable of interest is the interaction between SUE and the presence of LTG forecasts (DLTGISS). Following Cao and Narayanamoorthy (2012), I define SUE as current earnings minus earnings from the corresponding quarter one year ago, scaled by the previous fiscal quarter's closing market capitalization[6]. DLTGISS is an indicator variable that equals to one if more than one analyst issues LTG forecast for the firm in the month prior to the month of quarter t earnings announcement. The definitions of variables are summarized in Table 2.

4.3 Research design

4.3.1 Determinants of the firm-level presence of LTG forecasts

[6] There are two general ways to calculate SUE: random-walk-based SUE and analyst-based SUE. I focus in this paper on the random-walk-based SUE. Several studies show that there is a difference between random-walk-based and analyst-based PEAD (Livnat and Mendenhall, 2006; Ayers, Li and Yeung, 2011; Kovacs, 2015): the random walk-based PEAD is likely a result of investors misestimating the time-series properties of earnings, while the analyst-based PEAD is likely caused by longer price discovery process after earnings announcements. Thus, my results may not extend to analyst-based PEAD.

To better understand the properties of LTG forecasts, I examine the determinants of LTG forecasts in chapter 5 (basic characteristics of LTG forecasts) before my formal hypothesis testing. I follow Zhang (2008), and estimate the following logit model with standard errors clustered at the firm-level:

$$Prob(DLTGISS_{i,t} = 1) = f(\alpha_0 + \alpha_1 LNSIZE_{i,t} + \alpha_2 AGE_{i,t} + \alpha_3 EVOL_{i,t} + \alpha_4 ALTMANZ_{i,t} + \alpha_5 LOSS_{i,t} + \alpha_6 MERGE_{i,t} + \alpha_7 SPECIAL_{i,t} + \alpha_8 STENUM_{i,t} + \alpha_9 QTR4_{i,t} + \alpha_{10} BNEWS_{i,t} + \alpha_{11} BM_{i,t} + \alpha_{12} DRD_{i,t} + \alpha_{13} INST_{i,t} + \alpha_{14} EXP_{i,t} + \alpha_{15} NUMFIRM_{i,t} + \alpha_{16} DCFISS_{i,t} + \alpha_{17} BSIZE_{i,t} + \alpha_{18} LNVOLUME_{i,t} + \alpha_{19} PERCLTG_{i,t} + Year\ Controls + Industry\ Controls + \varepsilon_{i,t}) \quad (0)$$

The variables in model 0 are discussed in Appendix A. The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average firm-level presence of LTG forecasts. Throughout the analysis, all continuous explanatory variables are winsorized by calendar quarter at the 1st and the 99th percentile to mitigate the influence of outliers.

4.3.2 Test of H1

To examine whether the presence of LTG forecasts is associated with PEAD returns (H1), I follow Zhang (2012), and estimate the following model using ordinary least squares regression with standard errors clustered at the firm-level:

$$ARQ_{i,t+1} = \alpha_0 + \alpha_1 PSUE_{i,t} + \alpha_2 DLTGISS_{i,t} + \alpha_3 PSUE_{i,t} * DLTGISS_{i,t} + PSUE_{i,t} * (\alpha_4 PSIZE_{i,t} + \alpha_5 PDISP_{i,t} + \alpha_6 PPRICE_{i,t} + \alpha_7 PINST_{i,t} + \alpha_8 LOSS_{i,t} + \alpha_9 QTR4_{i,t} + \alpha_{10} PEVOL_{i,t} + \alpha_{11} DSTERESP_{i,t}) + \alpha_{12} PSIZE_{i,t} + \alpha_{13} PDISP_{i,t} + \alpha_{14} PPRICE_{i,t} + \alpha_{15} PINST_{i,t} + \alpha_{16} LOSS_{i,t} + \alpha_{17} QTR4_{i,t} + \alpha_{18} PEVOL_{i,t} + \alpha_{19} DSTERESP_{i,t} + Year\ Controls + Industry\ Controls + \varepsilon_{i,t+1} \quad (1)$$

The main variable of interest in model 1 is the interaction between SUE deciles (PSUE) and DLTGISS. The α3 coefficient indicates the association between the firm-level presence of LTG forecasts and PEAD returns. If the presence of LTG forecasts is associated with lower PEAD returns, we should observe that α3 in model 1 is negative and significant.

Following prior literature (Zhang, 2012), I construct PSUE by transferring SUE into decile ranks by calendar quarters using cut-off values from the previous quarter, and then scaling to the range -0.5 to 0.5. This transformation enables the coefficient on PSUE to be interpreted as the size-adjusted return from a zero investment strategy that longs the highest SUE decile and shorts the lowest SUE decile.

I include in model 1 several control variables, as well as their interactions with PSUE, that prior studies have identified as being associated with PEAD. These control variables are: firm size (PSIZE), analyst forecast dispersion (PDISP), price (PPRICE), institutional ownership (PINST), loss (LOSS), the fourth fiscal quarter (QTR4), earnings volatility (PEVOL), and short-term forecast responsiveness (DSTERESP). All control variables are transferred into decile ranks the same way as PSUE. The control variables PSIZE and PDISP are to capture information uncertainty (Zhang, 2012). PPRICE is to capture transaction costs (Bhushan, 1994). INST is to capture investor sophistication (Bartov, Radhakrishnan and Krinsky, 2000). LOSS, QTR4, PEVOL are to capture cross-sectional variations in SUE persistence (Rangan and Sloan, 1998; Narayanamoorthy, 2006; Cao and Narayanamoorthy, 2011). DSTERESP is to capture analysts' short-term forecast responsiveness (Zhang, 2008).

The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average size-adjusted returns.

4.3.3 Test of H2

To examine whether the magnitude of PEAD is smaller for firms with responsive LTG forecast revisions (H2), I estimate the following model using ordinary least squares regression with standard errors clustered at the firm-level, in a sample of firms that have responsiveness analysts' short-term forecasts:

$$ARQ_{i,t+1} = \alpha_0 + \alpha_1 PSUE_{i,t} + \alpha_2 DLTGRESP_{i,t} + \alpha_3 PSUE_{i,t} * DLTGRESP_{i,t} + PSUE_{i,t} * (\alpha_4 PSIZE_{i,t} + \alpha_5 PDISP_{i,t} + \alpha_6 PPRICE_{i,t} + \alpha_7 PINST_{i,t} + \alpha_8 LOSS_{i,t} + \alpha_9 QTR4_{i,t} + \alpha_{10} PEVOL_{i,t} + \alpha_{11} DSTERESP_{i,t}) + \alpha_{12} PSIZE_{i,t} + \alpha_{13} PDISP_{i,t} + \alpha_{14} PPRICE_{i,t} + \alpha_{15} PINST_{i,t} + \alpha_{16} LOSS_{i,t} + \alpha_{17} QTR4_{i,t} + \alpha_{18} PEVOL_{i,t} + \alpha_{19} DSTERESP_{i,t} + Year\ Controls + Industry\ Controls + \varepsilon_{i,t+1} \quad (2)$$

The main variable of interest in model 2 is the interaction between SUE deciles (PSUE) and DLTGRESP. The α3 coefficient indicates the association between the responsiveness of LTG forecasts and PEAD returns. If the responsiveness of LTG forecasts is associated with lower PEAD returns, we should observe that α3 in model 2 is negative and significant. All control variables are the same as in model 1. The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average size-adjusted returns.

4.3.4 Tests of H3a and H3b

4.3.4.1 Test of H3a

To examine whether analysts' short-term forecast revisions are timelier for firms with LTG forecasts (H3a), I follow Zhang (2008), and estimate the following logit model with standard errors clustered at the firm-level:

$$Prob(DSTERESP_{i,t} = 1) = f(\alpha_0 + \alpha_1 DLTGISS_{i,t} + \alpha_2 LNSIZE_{i,t} + \alpha_3 AGE_{i,t} + \alpha_4 EVOL_{i,t} + \alpha_5 ALTMANZ_{i,t} + \alpha_6 LOSS_{i,t} + \alpha_7 MERGE_{i,t} + \alpha_8 SPECIAL_{i,t} + \alpha_9 STENUM_{i,t} + \alpha_{10} QTR4_{i,t} + \alpha_{11} BNEWS_{i,t} + \alpha_{12} BM_{i,t} + \alpha_{13} DRD_{i,t} + \alpha_{14} INST_{i,t} + \alpha_{15} EXP_{i,t} + \alpha_{16} NUMFIRM_{i,t} + \alpha_{17} DCFISS_{i,t} + \alpha_{18} BSIZE_{i,t} + \alpha_{19} LNVOLUME_{i,t} + \alpha_{20} PERCLTG_{i,t} + Year\ Controls + Industry\ Controls + \varepsilon_{i,t}) \quad (3)$$

The main variable of interest in model 3 is DLTGISS. The α1 coefficient indicates the association between the presence of LTG forecasts and the likelihood of analysts' short-term forecast responsiveness. If the presence of LTG forecasts is associated with higher analysts' short-term forecast responsiveness, we should observe that α1 in model 3 is positive and significant. The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average firms' issuance of LTG forecasts. Throughout the analysis, all continuous explanatory variables are winsorized by calendar quarter at the 1st and the 99th percentile to mitigate the influence of outliers.

4.3.4.2 Test of H3b

To examine whether the correlation between analysts' short-term forecast errors and earnings surprises is smaller for firms with LTG forecasts (H3b), I estimate the following ordinary least squares regression with standard errors clustered at the firm-level:

$$FE_{i,t} = \alpha_0 + \alpha_1 SUE_{i,t} + \alpha_2 DLTGISS_{i,t} + \alpha_3 SUE_{i,t} * DLTGISS_{i,t} + Year\ Controls + Industry\ Controls + \varepsilon_{i,t} \quad (4)$$

Forecast errors are measured at two points in time. FE1 is measured at the first forecast revisions for quarter t+1 earnings issued after quarter t earnings announcement. FE2 is measured at the last forecast revisions for quarter t+1 earnings issued before quarter t+1 earnings announcement. The main variable of interest in model 4 is the interaction between SUE and DLTGISS. The α3 coefficient indicates the association between the presence of LTG forecasts and the correlation between analysts' forecast errors and SUE. If the presence of LTG forecasts is associated with lower correlation between analysts' forecast errors and SUE, we should observe that α3 in model 4 is negative and significant. The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average firms' issuance of LTG forecasts. Throughout the analysis, all continuous explanatory variables are winsorized by calendar quarter at the 1st and the 99th percentile to mitigate the influence of outliers.

4.3.5 Tests of H4a and H4b

4.3.5.1 Test of H4a

To examine whether the SUE persistence is lower for firms with LTG forecasts (H4a), I estimate the following model using ordinary least squares regression with standard errors clustered at the firm-level:

$$PSUE_{i,t+1} = \alpha_0 + \alpha_1 PSUE_{i,t} + \alpha_2 DLTGISS_{i,t} + \alpha_3 PSUE_{i,t} * DLTGISS_{i,t} + PSUE_{i,t} * (\alpha_4 PSIZE_{i,t} + \alpha_5 PDISP_{i,t} + \alpha_6 PPRICE_{i,t} + \alpha_7 PINST_{i,t} + \alpha_8 LOSS_{i,t} + \alpha_9 QTR4_{i,t} + \alpha_{10} PEVOL_{i,t} + \alpha_{11} DSTERESP_{i,t}) + \alpha_{12} PSIZE_{i,t} + \alpha_{13} PDISP_{i,t} + \alpha_{14} PPRICE_{i,t} + \alpha_{15} PINST_{i,t} + \alpha_{16} LOSS_{i,t} + \alpha_{17} QTR4_{i,t} + \alpha_{18} PEVOL_{i,t} + \alpha_{19} DSTERESP_{i,t} + Year\ Controls + Industry\ Controls + \varepsilon_{i,t+1} \quad (5)$$

The main variable of interest in model 5 is the interaction between PSUE and DLTGISS. The α3 coefficient indicates the association between the presence of LTG forecasts and the persistence of PSUE. If the presence of LTG forecasts is associated with lower SUE persistence, we should observe that α3 in model 5 is negative and significant. All control variables are the same as in model 1. The model includes fixed year and industry effects to account for cross-year and cross-industry differences in the average size-adjusted returns.

4.3.5.2 Test of H4b

To examine whether earnings expectations embedded in stock prices reflect the differences in SUE persistence for firms with and without LTG forecasts (H4b), I follow Cao and Narayanamoorthy (2012) and Collins, Gong and Hribar (2003), and use the Mishkin (1983) framework. Specifically, I compare the coefficients in the following equations, which are estimated simultaneously using a generalized nonlinear least squares estimation procedure:

$$PSUE_{i,t+1} = \alpha_0 + \alpha_1 PSUE_{i,t} + \alpha_2 DLTGISS_{i,t} + \alpha_3 PSUE_{i,t} * DLTGISS_{i,t} + \varepsilon_{i,t+1} \quad (6)$$

$$ARQ_{i,t+1} = \beta_0 + \beta_1 (PSUE_{i,t+1} - \alpha_0^* - \alpha_1^* PSUE_{i,t} - \alpha_2^* DLTGISS_{i,t} - \alpha_3^* PSUE_{i,t} * DLTGISS_{i,t}) + v_{i,t+1} \quad (7)$$

Model 6 is a forecasting equation in which α1 capture the persistence of SUE for firms without LTG forecasts, while α3 capture the incremental persistence of SUE for firms with LTG forecasts. Model 7 is a pricing equation that uses stock returns to infer the SUE persistence that investors perceive. α1* is the estimate of investors' perceived SUE persistence for firms without LTG forecasts, while α3* is the estimate of investors' perceived incremental SUE persistence for firms with LTG forecasts. The cross-equation restrictions are tested using a likelihood ratio test.

CHAPTER 5: BASIC CHARACTERISTICS OF LTG FORECASTS

5.1 Descriptive statistics

Table 3 presents descriptive statistics for the sample. Panel A shows the percentage of firm-quarters which have LTG forecasts by year. On average, 59.43% of the firm-quarters have more than one analyst who issue LTG forecasts. Although the percentage of firm-quarters which have LTG forecasts has been decreasing since 2002, as of 2013, still more than one-third (39.74%) of the firms continue to have LTG forecasts.

Panel B shows the percentage of firm-quarters which have LTG forecasts by industry. Across the 10 GICS industries, the utilities industry has the highest percentage of firm-quarters with LTG forecasts, followed by the consumer staples industry, while the healthcare industry has the lowest percentage (81.75%, 68.02% and 48.59%, respectively).[7]

Panel C provides summary statistics for the sample. On average, larger and older firms with less volatile earnings, higher short-term analyst following, higher institutional ownership, and higher trading volumes are more likely to have LTG forecasts. These firms also tend to have lower book-to-market ratio and lower R&D expenditures. The possibility that these firms have losses or negative earnings surprises is lower, while they are more likely to have recently been through an M&A or restructuring. The analysts who cover these firms are likely to be more experienced, work for larger brokerage firms and more likely to issue cash flow forecasts. Some of the variables examined in this panel have also been examined in Jung, Shane and Yang (2012),

[7] In untabulated analysis, I also look at the responsiveness of LTG forecasts across industries (for a sample of firms with LTG forecasts). Interestingly, I find that the telecommunication industry has the highest percentage of firm-quarters with responsive LTG forecasts, followed by healthcare industry, while the utilities industry has the lowest percentage. This suggests that the presence of LTG forecasts and the responsiveness (or efficiency) of these forecasts are different issues.

e.g., SIZE, BM, BSIZE. Except DCFISS, the summary statistics of the variables presented here is consistent with that presented in Jung, Shane and Yang (2012).

Panel D reports Spearman and Pearson correlations among variables. The correlations between DLTGISS and other variables are generally consistent with Panel C. It is worth noticing that three of the determinants (i.e., LNSIZE, STENUM and LNVOLUME) are highly correlated. The Spearman (Pearson) correlation between LNSIZE and LNVOLUME is 0.86 (0.87), between LNSIZE and STENUM is 0.74 (0.73), and between STENUM and LNVOLUME is 0.79 (0.76). This indicates a possible multicollinearity issue with my regression of the determinants of firm-level presence of LTG forecasts. To address this issue, in my determinants test, I check whether it makes a difference whether I include these variables one at a time in my regressions or include them all at once. However, as I only use these variables as control variables in my main regressions, it should not be a problem for estimating my main variables of interests (i.e., multicollinearity only affect the variables that are collinear).

5.2 Determinants of the firm-level presence of LTG forecasts

Table 4 reports the regression results examining the determinants of the firm-level presence of LTG forecasts. Compared with the results from the univariate analyses in Table 3, the signs and significance of some variables change after other variables are controlled for. In particular, in multivariable regressions reported in Table 4, the presence of LTG forecasts is shown to be negatively associated with AGE, positively associated with BNEWS and BM, and unassociated with ALTMANZ and MERGE. Untabulated results suggest that the changes of signs and significance of AGE, ALTMANZ, MERGE and BM are due to the controlling for LNSIZE. The change of sign of BNEWS is due to the controlling for LOSS.

CHAPTER 6: LTG FORECASTS AND PEAD RETURNS

6.1 Univariate analysis

Figure 1 depicts ARQ by the magnitude of earnings surprise and whether or not the firm has LTG forecasts in the month prior to the month of earnings announcement. Firms with LTG forecasts have significantly lower PEAD returns in the quarter after earnings announcement, suggesting more efficient return reactions for firms with LTG forecasts. The pattern is present for all SUE deciles, while strongest for the most positive decile.

Table 5 reports the average size-adjusted returns for portfolios formed based on SUE deciles and the presence of LTG forecasts. SUE deciles and the presence of LTG forecasts are independently sorted. For firms with LTG forecasts, the abnormal return is only significant for the highest SUE decile, while for firms without LTG forecasts, the abnormal returns are significant for almost all SUE deciles.

To better understand the nature of the differential PEAD returns between firms with and without LTG forecasts, I examine the drift at various horizons in Figure 2. I depict the difference in the average buy-and-hold size-adjusted returns between the top and bottom SUE decile from day 2 to day t after earnings announcements (t = 10, 20, …, 90). Firms with LTG forecasts have lower PEAD returns over all horizons. This suggests that the pattern documented in Figure 1 is not driven by any particular return-accumulation horizon.

6.2 Multivariate regressions

Table 6 reports the multivariate regression results testing the effect of firm-level presence of LTG forecasts on PEAD returns. The coefficient on PSUE in model 1a is 0.041, similar in magnitude to those reported in prior literature (e.g., Ayers, Li, Yeung, 2011). The coefficient on PSUE*DLTGISS is negative and significant (-0.038) in model 1b, indicating lower PEAD returns for firms with LTG forecasts. The results are robust after controlling for a wide range of variables shown in prior studies to be associated with PEAD (Model 1c).

CHAPTER 7: EXPLAINING THE LTG FORECAST EFFECT

7.1 Test of the forecast informativeness hypothesis

Table 7 reports the regression results testing whether the magnitude of PEAD is smaller for firms with responsive LTG forecast revisions. Firms with responsive LTG forecast revisions are also likely to have responsive analysts' short-term forecast revisions. To control for the responsiveness of analysts' short-term forecast revisions, this regression is carried out on a sample of firms with responsive analysts' short-term forecasts (i.e., analysts revise their short-term forecasts within two trading days after earnings announcements). The coefficient on PSUE is 0.028 in model 2a, much smaller than that in model 1a, suggesting lower PEAD returns for firms with responsive analysts' short-term forecasts. The coefficient on PSUE*DLTGRESP is negative and significant (-0.02) in model 1b, but lost its significance after adding the control variables in model 2c. Untabulated results show in a regression with only two interaction terms, PSUE*DLTGRESP and PSUE*PSIZE, the interaction with DLTGRESP is not significant. This suggests that DLTGRESP does not have any effect on PEAD return beyond the effect of size. These findings are inconsistent with my prediction that LTG forecasts convey information that mitigates PEAD. And these suggest that the forecast informativeness hypothesis is probably not the story that explains the negative association between the presence of LTG forecasts and PEAD returns.

7.2 Tests of the analyst ability hypothesis

7.2.1 The presence of LTG forecasts and short-term forecast responsiveness

Table 8 reports the regression results testing whether the presence of LTG forecasts is associated with analysts' short-term forecast responsiveness. The coefficient on DLTGISS is positive and significant (1.631) in model 3a. The results are robust after controlling for a wide range of variables shown in prior literature to affect DSTERESP (e.g., Zhang, 2008) in model 3b. This suggests that the presence of LTG forecasts is associated with higher analysts' short-term forecast responsiveness.

7.2.2 The presence of LTG forecasts and the correlation between analysts' forecast errors and SUE

Table 9 reports the regression results testing whether the presence of LTG forecasts is associated with the correlation between analysts' short-term forecast errors and SUE. The coefficients on SUE are positive and significant in model 4a and model 4c (i.e., 0.062, 0.053), suggesting that analysts do not efficiently incorporate past SUE in their short-term forecasts. The coefficients on SUE*DLTGISS are insignificant in model 4b and model 4d. This suggests that the presence of LTG forecasts is not associated with lower correlation between analysts' forecast errors and SUE. In other words, firms with LTG forecasts do not seem to have analysts who are more efficient in incorporating information in SUE.

7.2.3 Discussion

Overall, the results from testing of the analyst ability hypothesis have been mixed. On one hand, the presence of LTG forecasts is associated with more responsive analysts' short-term forecast revisions. On the other hand, the presence of LTG forecasts does not indicate that analysts are more efficient in incorporating SUE into their short-term forecasts. Zhang (2008) argues that forecast responsiveness and the correlation between forecast errors and SUE captures the two aspects of analysts' forecast efficiency: time and magnitude. She also demonstrates that the two aspects are separate and uncorrelated. However, in the context of my paper, if the presence of LTG forecasts predicts future PEAD returns solely due to its predictive power for future analysts' short-term forecast responsiveness. The relation between DLTGISS and PEAD returns should be not be apparent after control for DSTERESP, which is not the case as shown in model 1c. Untabulated results show that even within a sample of firms with responsive analysts' short-term forecasts, the ex-ante presence of LTG forecasts still identify firms with high versus low future PEAD returns. I also check that in the PEAD regression (model 1), how much the effect of DLTGISS changes after controlling for DSTERESP. Results (untabulated) show that after controlling for PSUE*DSTERESP, the coefficient on PSUE*DLTGISS goes down only slightly from -0.038 to -0.033. Thus, the effect of the presence of LTG forecasts on PEAD returns seems to be driven by something beyond the effect of analysts' short-term forecast responsiveness. In summary, I interpret the results presented here as not supporting the analyst ability hypothesis as an explanation for the negative relationship between the presence of LTG forecasts and PEAD returns.

7.3 Tests of the earnings persistence hypothesis

7.3.1 The presence of LTG forecasts and SUE persistence

Table 10 reports the regression results examining whether the persistence in earnings surprises is smaller for firms with LTG forecasts. Prior literature shows that investors fail to understand the cross-sectional variations in the persistence in earnings surprises, leading to predictable cross-sectional variations in PEAD returns (Rangan and Sloan, 1998; Narayanamoorthy, 2006). Thus, investors' failure to understand the negative relationship, if any, between the presence of LTG forecasts and the persistence in earnings surprises may be one potential explanation for the observed negative relationship between LTG forecasts and PEAD returns. Table 10 shows that the coefficient on PSUE is 0.384 in model 5a, which is comparable to these reported in prior literature (e.g., Cao and Narayanamoorthy, 2006). However, contrary to the prediction, the coefficient on PSUE*DLTGISS is positive and significant in both model 5b and model 5c (i.e., 0.015, 0.034). This suggests that the negative relationship between the presence of LTG forecasts and PEAD returns is not caused by investors not understanding the effect of LTG forecasts on the time-series properties of earnings.

7.3.2 Mishkin test

Table 11 reports the Mishkin test of the earnings expectations embedded in stock prices. Panel A presents the results from jointly estimating the earnings forecasting and the pricing equation on two subsamples (firms with and without LTG forecasts) separately. The likelihood ratio test reject that $\alpha1 = \alpha1^*$ for both samples. However, $\alpha1^*$ appear to be significantly larger for the sample of firms with LTG forecasts than for these without LTG forecasts (0.266 versus -0.038). Moreover, $\alpha1^*$ in the non-LTG forecast sample is not statistically significant. This suggests that while investors for the LTG forecast firm comprehend a great part of the implication of past earnings for future earnings, investors for the non-LTG forecast firms follow a random walk model and do not incorporate at all the implications of past SUE. Panel B presents the results from the full sample. The likelihood ratio test reject that $\alpha1 = \alpha1^*$, and that $\alpha1+\alpha3 = \alpha1^*+\alpha3^*$. This indicates that market underestimate the persistence of earnings surprises, for both the LTG forecast sample and the non-LTG forecast sample. Results also show that $(\alpha1 - \alpha1^*) / \alpha1$ is significantly larger than $((\alpha1+\alpha3) - (\alpha1^*+\alpha3^*)) / (\alpha1+\alpha3)$. This suggests that earnings expectations embedded in stock prices more accurately reflect the persistence of earnings surprise for firms with LTG forecasts.

7.3.3 Discussion

Overall, the results from SUE persistence tests suggest the following. First, SUE persistence is not lower, but higher, for firms with LTG forecasts. Second, the negative relationship between the presence of LTG forecasts and PEAD returns is not due to investors not understanding the effect of LTG forecasts on SUE persistence. On the contrary, it is related to more sophisticated investor understanding for the time-series properties of earnings for firms with LTG forecasts.

7.4 Controlling for the determinants of the presence of LTG forecasts

Table 12 Panel A reports the regression results examining the relationship between the presence of LTG forecasts and PEAD returns, after controlling for the observable determinants of DLTGISS identified in model 0, as well as their interactions with PSUE. The coefficient on PSUE*DLTGISS remain negative and significant (-0.024) in model 6a, suggesting that the relationship between DLTGISS and PEAD is not subsumed by any of the firm-level determinants of DLTGISS. Table 11 Panel B reports the PEAD regression results replacing DLTGISS with RESIDUAL, the residual from the logit regression of DLTGISS on all of its determinants. The coefficient on PSUE*RESIDUAL is negative and significant (-0.02) in model 6b, suggesting that the relationship between DLTGISS and PEAD is driven by the part of information in DLTGISS that is orthogonal to its determinants.

CHAPTER 8: CONCLUSION

This study examines whether and why the firm-level presence of LTG forecasts is associated with future PEAD returns. Using a sample of firm-quarters from 1995 to 2013 with analysts' short-term forecasts, I find that the magnitude of PEAD is significantly smaller for firms with LTG forecasts. I further explore three non-exclusive hypotheses about the sources of this return predictability. Results suggest that the negative relationship between the presence of LTG forecasts and PEAD returns is not driven by LTG forecasts playing a direct role in facilitating market efficiency. Further, results are inconsistent with the association between the presence of LTG forecasts and analysts' short-term forecast ability as an explanation for the relationship. Finally, there is no indication that the association between the presence of LTG forecasts and the time-series properties of earnings drives the results. The results are robust after controlling for a wide range of explanatory variables for PEAD returns or for the presence of LTG forecasts. I conclude that the finding of a negative relationship between the presence of LTG forecasts and PEAD returns documented in this study may be due to the presence of LTG forecasts capturing some unobservable firm characteristics which are not captured by proxies identified in prior studies. And I leave the further investigation of these characteristics to future research.

To summarize, this study documents a negative relationship between the firm-level presence of LTG forecasts and PEAD returns, and investigates several hypotheses that are expected to explain this relationship. The findings from this study extend the PEAD literature by identifying a novel analyst-based predictor of the cross-sectional variations in PEAD returns. This study also advances our understanding of LTG forecasts by identifying the following new determinants of the presence of these forecasts: earnings volatility, R&D intensity, trading volume, restructuring and fourth quarter earnings announcements.

FIGURES AND TABLES

FIGURE 1

Timeline for Measurement of Variables

This graph illustrates the timeline for measurement of variables. See Table 2 for variable definitions.

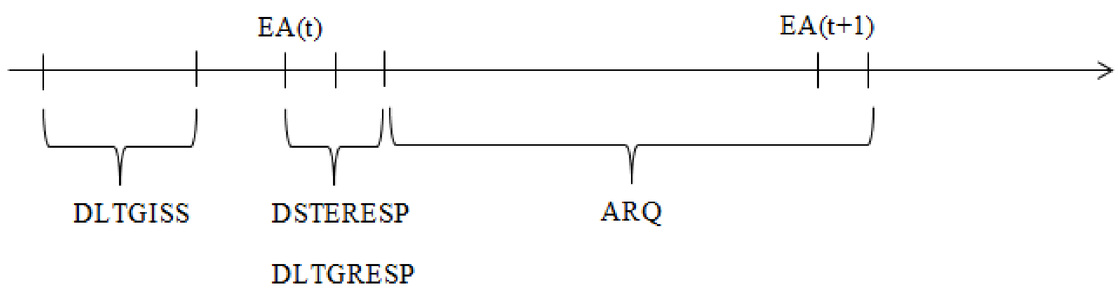

FIGURE 2

PEAD Returns With and Without LTG Forecasts

This figure depicts ARQ by the magnitude of earnings surprise and whether or not the firm has LTG forecasts in the month prior to the month of earnings announcement. The x-axis represents the ten earnings surprise deciles. The y-axis represents the size-adjusted buy-and-hold abnormal return from two days after quarter t earnings announcement through one day after quarter t+1 earnings announcement. See Table 2 for variable definitions.

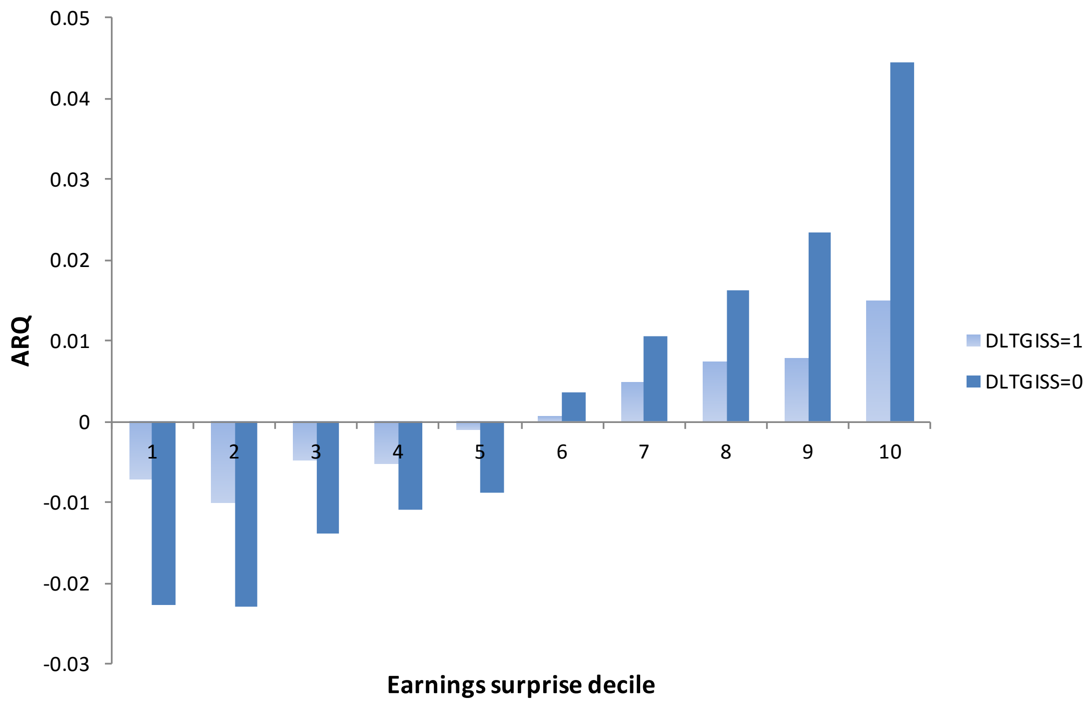

FIGURE 3

Performance of Drift at Different Horizons

This figure depicts the difference in ARQ between top and bottom SUE decile over different time horizons (after earnings announcement) by whether or not the firm has LTG forecasts in the month prior to the month of earnings announcement. The x-axis represents the number of days after the earnings announcement date. The y-axis represents the difference in ARQ between top and bottom SUE decile, averaged over 76 calendar quarters from 1995 till 2013. See Table 2 for variable definitions.

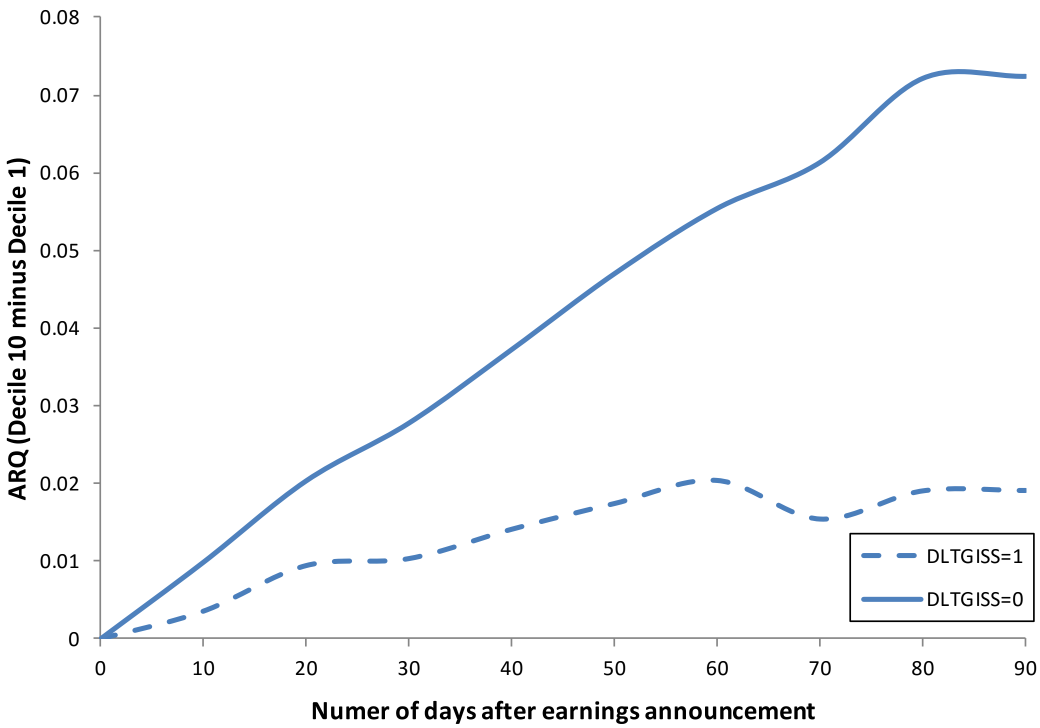

TABLE 1

Sample Selection

This table reports the sample selection procedures. Data are firm-quarter observations from 1995 to 2013.

All Compustat-CRSP merged database firm-quarters between 1995 and 2013	483,559	100%
Drop observations with more than one earnings announcement on the same date for the same firm	(1,120)	0%
Drop if current earnings announcement is less than 35 days or more than 150 days away from the previous earnings announcement	(7,929)	-2%
Drop observations whose current quarter earnings announcement date is on/before or more than 95 days after current quarter fiscal period end date	(3,323)	-1%
Drop observations that do not have quarterly earnings forecasts from I/B/E/S	(171,104)	-35%
Drop observations that do not have matching stock returns from CRSP	(42,132)	-9%
Drop observations with missing SUE	(34,016)	-7%
Drop penny stocks (stocks with price lower than $1)	(2,891)	-1%
Drop the first announcement if two earnings announcements occur in the same calendar quarter for the same firm	(1,946)	0%
Total	219,098	45%

TABLE 2

Variable Definition

This table summarizes variable definitions.

Variables	Descriptions
Main variables:	
ARQ	Size-adjusted buy-and-hold return in the drift window, defined as the raw return (two days after quarter t earnings announcement date through one day after quarter t+1 earnings announcement date) adjusted for the same period returns for the size decile for which the firm belongs (where size deciles are determined by the total market capitalizations on the earnings announcement date)
SUE	Standard unexpected earnings, defined as quarter t's EPS minus quarter t-4's EPS, scaled by the stock price at the end of quarter t-1
PSUE	SUE deciles, defined as SUE transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range -0.5 to 0.5
FPSUE	SUE deciles for quarter t+1
DLTGISS	= 1 if more than one analyst issues LTG forecasts for firm i in the month prior to the month of quarter t earnings announcement, and 0 otherwise
DLTGRESP	=1 if at least one analyst revises her LTG forecast for firm i within two trading days after quarter t earnings announcement (i.e., trading days 0 and 1 with respect to the announcement date), and 0 otherwise
DSTERESP	=1 if at least one analyst revises her forecast for quarter t+1 of firm i within two trading days after quarter t earnings announcement (i.e., trading days 0 and 1 with respect to the announcement date), and 0 otherwise
ABSFE1	Median absolute forecast error measured at the first forecast revisions for quarter t+1 issued after quarter t earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t
ABSFE2	Median absolute forecast error measured at the last forecast revisions for quarter t+1 issued before quarter t+1 earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t
FE1	Median forecast error measured at the first forecast revisions for quarter t+1 issued after quarter t earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t
FE2	Median forecast error measured at the last forecast revisions for quarter t+1 issued before quarter t+1 earnings announcement; where forecast error is calculated as the I/B/E/S actual EPS for quarter t+1 minus individual analysts' forecast for quarter t+1, scaled by the stock price at the end of fiscal quarter t
Control variables:	
SIZE	Market capitalization at the end of fiscal quarter t
PSIZE	SIZE deciles, defined as SIZE transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range -0.5 to 0.5
DISP	Analyst forecast dispersion, defined as the standard deviation of one-quarter-ahead analyst forecasts divided by the stock price at the end of fiscal quarter t
PDISP	DISP deciles, defined as DISP transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range -0.5 to 0.5
PRICE	Market price per share at the end of fiscal quarter t
PPRICE	PRICE deciles, defined as PRICE transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range -0.5 to 0.5
INST	Institutional ownership, defined as the percent of firm i's common shares held by institutional investors for the quarter before quarter t earnings announcement; where the institutional ownership information is obtained from CDA/Spectrum, and missing institutional ownership data is counted as zero

TABLE 2 (Continued)

Variable Definition

This table summarizes variable definitions.

Variables	Descriptions
PINST	INST deciles, defined as INST transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range -0.5 to 0.5
LOSS	= 1 if quarter t's earnings are negative, and 0 otherwise
QTR4	= 1 if quarter t is the fourth quarter of the fiscal year, and 0 otherwise
EVOL	Earnings volatility, defined as the standard deviation of the most recent eight quarterly earnings (including quarter t), while quarterly earnings are deflated by average total assets
PEVOL	EVOL deciles, defined as EVOL transferred into decile ranks within each calendar quarter using the cut-off values from the previous quarter, and then scaled to the range -0.5 to 0.5
LNSIZE	The natural logarithm of SIZE
AGE	Number of years firm i has been publicly traded, per CRSP files
ALTMANZ	Altman's (1968) Z-score, defined as 1.2*net working capital/total assets + 1.4*retained earnings/total assets + 3.3*earnings before interest and taxes/total assets + 0.6*market value of equity/book value of liabilities + 1*sales/total assets
MERGE	= 1 if firm i experienced a merger or acquisition in quarter t, and 0 otherwise; where mergers or acquistions are identified by quarterly footnote 1 of AA in compustat
SPECIAL	= 1 if firm i reports negative special items in quarter t, and 0 otherwise
STENUM	Number of analysts who issue one-quarter-ahead forecasts for firm i at the month of quarter t earnings announcement
BNEWS	= 1 if the SUE of firm i in quarter t is negative, and 0 otherwise
BM	Book-to-market ratio, defined as the book value of equity at the end of quarter t divided by the market value at the end of the same quarter
RD	R&D intensity, defined as R&D expense divided by market capitalization at the end of quarter t; where missing R&D is counted as zero
DRD	= 1 if RD does not equal zero, and 0 otherwise
EXP	Median firm-specific experience of analysts who follow firm i for quarter t; where experience is measured as the number of years for which an analyst has followed the firm
NUMFIRM	Median number of firms followed by analysts who follow firm i in quarter t
PERCLTG	Median likelihood of issuancing LTG forecasts for analysts who follow firm i in quarter t; where likelihood for each analyst is measured as number of LTG forecasts the analyst issues minus one (other than the LTG forecast issued for firm i), divided by the total number of firms followed by the analyst minus one (other than firm i)
DCFISS	= 1 if at least one analyst issues a cash flow forecast for firm i in the month prior to the month of quarter t earnings announcement, and 0 otherwise
BSIZE	Median size of the brokerage houses employing analysts who follow firm i for quarter t; where the brokerage house size is measured as the number of distinct analysts providing forecasts in the brokerage house
LNVOLUME	The natural logarithm of the dollar trading volume in the year prior to the year of quarter t earnings announcement; where dollar trading volume is measured as the absolute value of month-end stock price multiply by the trading volume during the month, summed over the 12 months
RESIDUAL	The residual from estimating model 0

TABLE 3

Descriptive Statistics

This table provides summary statistics for my sample. See Table 2 for variable definitions. Panel A reports the LTG forecast issuance by year. Panel B reports the LTG forecast issuance by Compustat industry. Panel C reports the summary statistics. Panel D reports correlations among variables. Spearman (Pearson) correlations are presented above (below) the diagonal. Correlations that are significant at the 1% significance level are marked in bold.

Panel A: LTG forecast issuance by year

Year	N (Total)	N (DLTGISS=1)	% (DLTGISS=1)
1995	10,017	6,663	66.52%
1996	11,112	7,565	68.08%
1997	12,395	8,676	70.00%
1998	13,247	9,169	69.22%
1999	13,084	9,025	68.98%
2000	12,494	8,223	65.82%
2001	11,953	7,622	63.77%
2002	11,576	7,892	68.18%
2003	11,462	7,659	66.82%
2004	11,628	7,093	61.00%
2005	11,666	7,021	60.18%
2006	11,699	6,817	58.27%
2007	11,747	6,517	55.48%
2008	11,400	6,021	52.82%
2009	11,266	5,327	47.28%
2010	11,357	4,915	43.28%
2011	10,591	5,192	49.02%
2012	10,091	4,710	46.68%
2013	10,313	4,098	39.74%
Overall	219,098	130,205	59.43%

Panel B: LTG forecast issuance by industry

Sector	N (Total)	N (DLTGISS=1)	% (DLTGISS=1)
Energy	11,070	5,905	53.34%
Materials	10,663	6,185	58.00%
Industrials	29,662	18,024	60.76%
Consumer Discretionary	36,823	24,856	67.50%
Consumer Staples	8,695	5,914	68.02%
Health Care	30,980	15,052	48.59%
Financials	36,290	18,246	50.28%
Information Technology	45,024	28,727	63.80%
Telecommunication Services	3,298	1,906	57.79%
Utilities	6,593	5,390	81.75%
Overall	219,098	130,205	59.43%

TABLE 3 (Continued)

Descriptive Statistics

This table provides summary statistics for my sample. See Table 2 for variable definitions. Panel A reports the LTG forecast issuance by year. Panel B reports the LTG forecast issuance by Compustat industry. Panel C reports the summary statistics. Panel D reports correlations among variables. Spearman (Pearson) correlations are presented above (below) the diagonal. Correlations that are significant at the 1% significance level are marked in bold.

Panel C: Summary statistics

	DLTGISS=1						DLTGISS=0						Total			
	N	Mean	Std. Dev.	Q1	Median	Q3	N	Mean	Std. Dev.	Q1	Median	Q3	N	Mean	Std. Dev.	Median
ARQ	130,205	0.001	0.234	-0.113	-0.006	0.101	88,893	0.003	0.319	-0.140	-0.016	0.111	219,098	0.002	0.272	-0.010
SUE	130,205	-0.001	0.051	-0.004	0.002	0.005	88,893	0.001	0.083	-0.009	0.001	0.010	219,098	0.000	0.066	0.002
DLTGRESP	130,205	0.268	0.443	0.000	0.000	1.000	88,893	0.041	0.199	0.000	0.000	0.000	219,098	0.176	0.381	0.000
DSTERESP	130,205	0.732	0.443	0.000	1.000	1.000	88,893	0.510	0.500	0.000	1.000	1.000	219,098	0.642	0.479	1.000
ABSFE1	120,612	0.008	0.054	0.000	0.001	0.003	67,278	0.026	0.108	0.001	0.004	0.012	187,890	0.014	0.078	0.002
ABSFE2	120,612	0.007	0.048	0.000	0.001	0.003	67,278	0.024	0.099	0.001	0.003	0.011	187,890	0.013	0.071	0.001
FE1	120,612	-0.002	0.037	-0.001	0.000	0.001	67,278	-0.007	0.074	-0.003	0.000	0.003	187,890	-0.004	0.053	0.000
FE2	120,612	-0.001	0.034	0.000	0.000	0.001	67,278	-0.006	0.069	-0.003	0.000	0.004	187,890	-0.003	0.049	0.000
LNSIZE	130,205	7.130	1.672	5.953	7.024	8.213	88,893	5.381	1.330	4.424	5.297	6.226	219,098	6.420	1.766	6.281
AGE	130,202	18.839	18.267	6.000	12.000	27.000	88,892	13.959	12.799	5.000	10.000	18.000	219,094	16.859	16.447	11.000
EVOL	112,565	0.016	0.025	0.004	0.008	0.017	75,988	0.027	0.038	0.004	0.012	0.031	188,553	0.020	0.032	0.009
ALTMANZ	107,574	4.548	7.183	1.317	2.466	4.927	69,231	4.149	8.019	0.834	2.118	4.657	176,805	4.391	7.524	2.338
LOSS	130,205	0.166	0.372	0.000	0.000	0.000	88,893	0.358	0.480	0.000	0.000	1.000	219,098	0.244	0.430	0.000
MERGE	130,205	0.021	0.142	0.000	0.000	0.000	88,893	0.007	0.085	0.000	0.000	0.000	219,098	0.015	0.122	0.000
SPECIAL	130,205	0.284	0.451	0.000	0.000	1.000	88,893	0.239	0.426	0.000	0.000	0.000	219,098	0.266	0.442	0.000
STENUM	129,965	8.794	6.165	4.000	7.000	12.000	88,301	3.145	3.051	1.000	2.000	4.000	218,266	6.508	5.838	5.000
QTR4	130,205	0.244	0.430	0.000	0.000	0.000	88,893	0.231	0.422	0.000	0.000	0.000	219,098	0.239	0.426	0.000
BNEWS	130,205	0.381	0.486	0.000	0.000	1.000	88,893	0.440	0.496	0.000	0.000	1.000	219,098	0.405	0.491	0.000
BM	129,906	0.509	0.403	0.262	0.429	0.651	88,811	0.646	0.542	0.307	0.549	0.852	218,717	0.565	0.469	0.471
RD	130,205	0.005	0.013	0.000	0.000	0.005	88,893	0.010	0.020	0.000	0.000	0.012	219,098	0.007	0.016	0.000
INST	130,205	0.650	0.249	0.476	0.680	0.838	88,893	0.466	0.287	0.221	0.433	0.695	219,098	0.575	0.280	0.598
PERCLTG	130,063	0.421	0.183	0.286	0.417	0.545	88,047	0.290	0.264	0.000	0.250	0.481	218,110	0.368	0.229	0.370
EXP	130,063	2.349	1.712	1.000	2.000	3.000	88,047	2.003	1.960	1.000	1.500	3.000	218,110	2.209	1.824	2.000
NUMFIRM	130,063	16.706	5.204	14.000	16.000	18.500	88,047	16.676	6.385	13.000	16.000	19.500	218,110	16.694	5.710	16.000
DCFISS	130,205	0.392	0.488	0.000	0.000	1.000	88,893	0.174	0.379	0.000	0.000	0.000	219,098	0.303	0.460	0.000
BSIZE	130,063	51.687	29.573	30.000	47.000	65.000	88,047	36.428	28.524	17.000	28.500	48.000	218,110	45.527	30.100	39.000
LNVOLUME	130,169	16.711	1.913	15.357	16.713	18.066	88,814	14.607	1.868	13.241	14.504	15.855	218,983	15.857	2.159	15.842

TABLE 3 (Continued)

Descriptive Statistics

This table provides summary statistics for my sample. See Table 2 for variable definitions. Panel A reports the LTG forecast issuance by year. Panel B reports the LTG forecast issuance by Compustat industry. Panel C reports the summary statistics. Panel D reports correlations among variables. Spearman (Pearson) correlations are presented above (below) the diagonal. Correlations that are significant at the 1% significance level are marked in bold.

Panel D: Pearson (below), Spearman (above) Correlations

	DLTGISS	ARQ	SUE	DLTGRESP	DSTERESP	FE1	LNSIZE	AGE	EVOL	ALTMANZ	LOSS	MERGE	SPECIAL	STENUM	QTR4	BNEWS	BM	RD	INST	PERCLTG	EXP	NUMFIRM	DCFISS	BSIZE	LNVOLUME
DLTGISS	1.00	**0.02**	0.00	**0.29**	**0.23**	**-0.01**	**0.50**	**0.11**	**-0.15**	**0.09**	**-0.22**	**0.05**	**0.05**	**0.57**	**0.02**	**-0.06**	**-0.14**	**-0.09**	**0.32**	**0.29**	**0.15**	**0.02**	**0.23**	**0.31**	**0.48**
ARQ	0.00	1.00	**0.06**	**0.03**	**0.02**	**0.28**	**0.05**	**0.04**	**-0.05**	0.00	**-0.07**	**0.02**	**0.01**	**0.03**	**0.05**	**-0.06**	**0.02**	**-0.01**	**0.05**	**0.02**	**0.02**	**0.01**	**0.04**	**0.02**	**0.02**
SUE	**-0.01**	**0.03**	1.00	0.00	**-0.01**	**0.11**	**0.04**	**0.01**	**-0.03**	**0.04**	**-0.34**	**0.03**	**-0.16**	0.00	**0.01**	**-0.85**	**-0.10**	**-0.04**	**0.02**	**0.02**	**-0.03**	**0.02**	**-0.01**	**-0.02**	**-0.05**
DLTGRESP	**0.29**	**0.01**	0.00	1.00	**0.28**	**0.03**	**0.36**	**0.11**	**-0.07**	**0.07**	**-0.12**	**-0.02**	**0.09**	**0.41**	**0.02**	**-0.03**	**-0.12**	**-0.01**	**0.26**	**0.17**	**0.13**	**-0.03**	**0.29**	**0.18**	**0.39**
DSTERESP	**0.23**	0.00	0.00	**0.28**	1.00	**0.04**	**0.41**	**0.13**	**0.01**	**0.04**	**-0.03**	**-0.05**	**0.15**	**0.54**	**-0.07**	**0.01**	**-0.10**	**0.06**	**0.43**	**0.04**	**0.16**	**-0.04**	**0.33**	**0.22**	**0.48**
FE1	**0.04**	**0.11**	**0.09**	**0.03**	**0.01**	1.00	**0.03**	0.00	**0.04**	-0.01	**-0.03**	**-0.01**	**0.03**	**0.04**	**0.03**	**-0.08**	**-0.02**	**0.07**	**0.05**	**-0.01**	**0.01**	**-0.01**	**0.04**	**0.02**	**0.04**
LNSIZE	**0.49**	0.00	**0.03**	**0.38**	**0.40**	**0.07**	1.00	**0.40**	**-0.24**	**0.11**	**-0.28**	**0.03**	**0.15**	**0.74**	**0.01**	**-0.11**	**-0.31**	**-0.13**	**0.55**	**0.14**	**0.28**	**0.07**	**0.46**	**0.46**	**0.86**
AGE	**0.15**	**0.01**	0.01	**0.12**	**0.12**	**0.02**	**0.45**	1.00	**-0.20**	**-0.10**	**-0.19**	**-0.04**	**0.08**	**0.20**	**0.01**	**-0.03**	**0.06**	**-0.12**	**0.24**	**-0.02**	**0.39**	**0.12**	**0.20**	**0.11**	**0.32**
EVOL	**-0.17**	0.01	**0.03**	**-0.08**	**-0.03**	**-0.02**	**-0.22**	**-0.17**	1.00	**-0.02**	**0.44**	-0.001	**0.11**	**-0.10**	**-0.01**	**0.14**	**-0.20**	**0.42**	**-0.03**	**-0.04**	**-0.11**	**-0.27**	**-0.03**	**-0.09**	**-0.04**
ALTMANZ	**0.03**	**-0.02**	0.01	**0.01**	0.00	**0.02**	**0.07**	**-0.14**	**0.01**	1.00	**-0.21**	**0.09**	**-0.15**	**0.09**	0.00	**-0.11**	**-0.30**	**0.15**	**0.06**	**0.07**	**-0.16**	**-0.14**	**-0.09**	**-0.15**	**0.08**
LOSS	**-0.22**	**-0.02**	**-0.20**	**-0.12**	**-0.03**	**-0.09**	**-0.27**	**-0.17**	**0.37**	**-0.04**	1.00	**-0.03**	**0.18**	**-0.14**	**0.03**	**0.35**	**0.02**	**0.31**	**-0.15**	**-0.12**	**-0.08**	**-0.11**	**-0.06**	**-0.05**	**-0.12**
MERGE	**0.05**	**0.02**	**0.01**	**-0.02**	**-0.05**	**0.01**	**0.03**	**-0.03**	0.00	**0.10**	**-0.03**	1.00	0.001	**0.01**	**-0.01**	**-0.04**	**-0.08**	0.00	**-0.03**	**0.05**	**-0.06**	**0.01**	**-0.06**	**-0.01**	0.00
SPECIAL	**0.05**	**0.01**	**-0.10**	**0.09**	**0.15**	0.00	**0.15**	**0.08**	**0.07**	**-0.11**	**0.18**	0.00	1.00	**0.16**	**0.09**	**0.17**	**0.02**	**0.11**	**0.19**	**-0.01**	**0.10**	**-0.05**	**0.16**	**0.12**	**0.21**
STENUM	**0.47**	0.00	0.00	**0.45**	**0.45**	**0.04**	**0.73**	**0.23**	**-0.10**	**0.03**	**-0.14**	0.00	**0.15**	1.00	**-0.01**	**-0.04**	**-0.23**	**-0.02**	**0.55**	**0.15**	**0.24**	**0.01**	**0.51**	**0.38**	**0.79**
QTR4	**0.02**	**0.03**	0.00	**0.02**	**-0.07**	**0.03**	**0.01**	**0.01**	0.00	**-0.01**	**0.03**	**-0.01**	**0.09**	**-0.01**	1.00	0.00	-0.01	**0.09**	0.00	0.00	**0.03**	**0.01**	**0.01**	**0.01**	**0.02**
BNEWS	**-0.06**	**-0.04**	**-0.36**	**-0.03**	**0.01**	**-0.06**	**-0.11**	**-0.02**	**0.07**	**-0.05**	**0.35**	**-0.04**	**0.17**	**-0.04**	0.00	1.00	**0.15**	**0.08**	**-0.04**	**-0.05**	**0.02**	**-0.03**	0.00	**0.01**	0.00
BM	**-0.14**	**0.02**	**-0.10**	**-0.11**	**-0.09**	**-0.15**	**-0.32**	**-0.01**	**-0.11**	**-0.22**	**0.10**	**-0.06**	**0.03**	**-0.19**	**-0.01**	**0.15**	1.00	**-0.20**	**-0.11**	**-0.08**	**0.14**	**0.15**	**-0.09**	**-0.05**	**-0.25**
RD	**-0.14**	**0.05**	**-0.03**	**-0.06**	**0.01**	0.00	**-0.22**	**-0.11**	**0.35**	**-0.08**	**0.36**	**-0.01**	**0.10**	**-0.08**	**0.07**	**0.11**	0.00	1.00	**-0.03**	**-0.07**	**-0.09**	**-0.20**	**-0.06**	**-0.09**	**0.03**
INST	**0.32**	**0.01**	0.00	**0.25**	**0.43**	**0.04**	**0.51**	**0.20**	**-0.13**	**-0.01**	**-0.15**	**-0.03**	**0.18**	**0.45**	0.00	**-0.04**	**-0.12**	**-0.10**	1.00	**0.08**	**0.24**	**-0.04**	**0.39**	**0.29**	**0.61**
PERCLTG	**0.28**	**0.01**	0.00	**0.16**	**0.04**	**0.02**	**0.13**	**0.02**	**-0.07**	**0.01**	**-0.12**	**0.04**	**-0.01**	**0.10**	0.00	**-0.05**	**-0.09**	**-0.09**	**0.08**	1.00	**-0.03**	**-0.05**	0.00	**0.05**	**0.13**
EXP	**0.09**	0.00	0.00	**0.08**	**0.10**	0.00	**0.24**	**0.35**	**-0.11**	**-0.16**	**-0.07**	**-0.05**	**0.08**	**0.16**	**0.02**	**0.02**	**0.12**	**-0.05**	**0.18**	**-0.04**	1.00	**0.25**	**0.21**	**0.21**	**0.26**
NUMFIRM	0.00	-0.01	0.00	**-0.05**	**-0.11**	**-0.01**	**0.02**	**0.12**	**-0.14**	**-0.11**	**-0.11**	**0.02**	**-0.07**	**-0.06**	0.00	**-0.03**	**0.09**	**-0.11**	**-0.11**	**-0.05**	**0.20**	1.00	**0.02**	**0.10**	**-0.03**
DCFISS	**0.23**	**0.01**	0.00	**0.29**	**0.33**	**0.02**	**0.46**	**0.23**	**-0.08**	**-0.09**	**-0.06**	**-0.06**	**0.16**	**0.51**	**0.01**	0.00	**-0.09**	**-0.08**	**0.38**	**0.01**	**0.15**	**-0.03**	1.00	**0.30**	**0.50**
BSIZE	**0.25**	**0.01**	**-0.01**	**0.13**	**0.16**	**0.01**	**0.37**	**0.17**	**-0.09**	**-0.09**	**-0.02**	**-0.02**	**0.11**	**0.22**	**0.01**	**0.01**	**-0.01**	**-0.05**	**0.23**	**0.03**	**0.16**	**0.02**	**0.26**	1.00	**0.43**
LNVOLUME	**0.48**	0.00	**-0.03**	**0.39**	**0.48**	**0.03**	**0.87**	**0.36**	**-0.07**	**0.05**	**-0.11**	0.00	**0.21**	**0.76**	**0.02**	0.00	**-0.22**	**-0.06**	**0.60**	**0.13**	**0.19**	**-0.09**	**0.50**	**0.34**	1.00

TABLE 4

Determinants of the Firm-Level Presence of LTG Forecasts

This table reports the regression results examining the determinants of the firm-level presence of LTG forecasts. See Table 2 for variable definitions. Models are estimated using logit regression with standard errors clustered at the firm-level. z-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

	(0)
	DLTGISS
Constant	-7.302***
	(-24.790)
LNSIZE	0.231***
	(8.117)
AGE	-0.011***
	(-5.982)
EVOL	-4.717***
	(-8.417)
ALTMANZ	-0.003
	(-1.143)
LOSS	-0.712***
	(-17.797)
MERGE	0.167
	(1.317)
SPECIAL	0.144***
	(4.705)
STENUM	0.308***
	(29.501)
QTR4	0.225***
	(15.670)
BNEWS	0.116***
	(5.525)
BM	0.164***
	(3.598)
DRD	-0.295***
	(-5.865)
INST	0.841***
	(8.830)
EXP	0.025**
	(2.483)
NUMFIRM	0.011***
	(3.047)
DCFISS	0.376***
	(7.469)
BSIZE	0.003***
	(5.365)
LNVOLUME	0.125***
	(6.569)
PERCLTG	1.737***
	(26.672)
Year dummies	Included
Industry dummies	Included
Observations	150,447

TABLE 5

Portfolios Formed Based on SUE Deciles and the Presence of LTG Forecasts

This table reports the average size-adjusted returns for portfolios formed based on SUE deciles and the presence of LTG forecasts (using independent sorting). See Table 2 for variable definitions. t-statistics are reported in parentheses, and are calculated as the time-series of the quarterly portfolio size-adjusted stock returns. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

	DLTGISS = 1	DLTGISS = 0
SUE deciles	ARQ	ARQ
Lowest	-0.007	-0.023
	(-0.797)	(-2.493)
2	-0.010	-0.023
	(-1.915)	(-4.172)
3	-0.005	-0.014
	(-1.188)	(-3.142)
4	-0.005	-0.011
	(-1.454)	(-2.810)
5	-0.001	-0.009
	(-0.352)	(-1.965)
6	0.001	0.004
	(0.265)	(0.742)
7	0.005	0.011
	(1.579)	(2.062)
8	0.007	0.016
	(1.797)	(3.693)
9	0.008	0.023
	(1.751)	(4.893)
Highest	0.015	0.044
	(2.115)	(3.819)
Difference	0.022	0.067
	(2.734)	(8.515)

TABLE 6

The Presence of LTG Forecasts and PEAD Returns

This table reports the regression results testing the relationship between the ex-ante presence of LTG forecast and PEAD returns. See Table 2 for variable definitions. Models are estimated using ordinary least squares regression with standard errors clustered at the firm-level. t-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

	(1a) ARQ	(1b) ARQ	(1c) ARQ
Constant	0.012***	0.012***	0.009***
	(5.228)	(4.993)	(3.125)
PSUE	0.041***	0.060***	0.060***
	(18.689)	(16.987)	(9.134)
DLTGISS		-0.001	-0.001
		(-0.473)	(-0.692)
PSUE*DLTGISS		-0.038***	-0.013**
		(-8.667)	(-2.253)
PSUE*PSIZE			-0.056***
			(-5.060)
PSUE*PDISP			0.005
			(0.580)
PSUE*PPRICE			0.052***
			(4.657)
PSUE*PINST			-0.060***
			(-7.165)
PSUE*LOSS			-0.014**
			(-2.170)
PSUE*QTR4			-0.025***
			(-5.009)
PSUE*PEVOL			-0.033***
			(-3.939)
PSUE*DSTERESP			-0.016***
			(-2.748)
PSIZE			-0.001
			(-0.181)
PDISP			-0.028***
			(-10.458)
PPRICE			-0.035***
			(-11.168)
PINST			0.007***
			(3.109)
LOSS			-0.007***
			(-3.029)
QTR4			0.021***
			(14.020)
PEVOL			0.005*
			(1.932)
DSTERESP			0.007***
			(3.528)
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	219,098	219,098	157,782
R-squared	0.005	0.005	0.010

TABLE 7

LTG Forecast Responsiveness and PEAD Returns

This table reports the regression results testing the relationship between the responsiveness of LTG forecast revisions after earnings announcements and PEAD returns. See Table 2 for variable definitions. Models are estimated using ordinary least squares regression with standard errors clustered at the firm-level. t-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

	(2a) ARQ	(2b) ARQ	(2c) ARQ
Constant	0.008***	0.005*	0.009***
	(2.855)	(1.944)	(2.963)
PSUE	0.028***	0.032***	0.031***
	(11.626)	(11.561)	(9.703)
DLTGRESP		0.007***	0.007***
		(4.893)	(4.592)
PSUE*DLTGRESP		-0.020***	-0.005
		(-3.866)	(-0.956)
PSUE*PSIZE			-0.053***
			(-5.219)
PSUE*PDISP			0.006
			(0.614)
PSUE*PPRICE			0.051***
			(4.408)
PSUE*PINST			-0.053***
			(-6.284)
PSUE*LOSS			-0.018***
			(-2.617)
PSUE*QTR4			-0.024***
			(-4.302)
PSUE*PEVOL			-0.024***
			(-2.757)
PSIZE			-0.002
			(-0.643)
PDISP			-0.023***
			(-8.152)
PPRICE			-0.029***
			(-9.075)
PINST			0.003
			(1.238)
LOSS			-0.005*
			(-1.878)
QTR4			0.018***
			(10.427)
PEVOL			0.007**
			(2.559)
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	140,278	140,278	120,092
R-squared	0.005	0.005	0.008

TABLE 8

The Presence of LTG Forecasts and Analysts' Short-Term Forecast Responsiveness

This table reports the regression results testing the relationship between ex-ante presence of LTG forecasts and the responsiveness of analysts' short-term forecast revisions after earnings announcements. See Table 2 for variable definitions. Models are estimated using logit regression with standard errors clustered at the firm-level. z-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

	(3a) DSTERESP	(3b) DSTERESP
Constant	0.638***	-3.051***
	(5.747)	(-14.002)
DLTGISS	1.631***	0.366***
	(50.060)	(11.434)
LNSIZE		-0.022
		(-1.019)
AGE		-0.004***
		(-3.559)
EVOL		0.070
		(0.166)
ALTMANZ		0.002
		(1.201)
LOSS		0.060**
		(2.002)
MERGE		-0.347***
		(-4.162)
SPECIAL		-0.025
		(-0.963)
STENUM		0.203***
		(31.645)
QTR4		-0.561***
		(-24.209)
BNEWS		0.066***
		(3.095)
BM		-0.009
		(-0.252)
DRD		0.249***
		(6.110)
INST		0.608***
		(8.264)
EXP		0.002
		(0.279)
NUMFIRM		0.014***
		(4.694)
DCFISS		0.068*
		(1.845)
BSIZE		0.003***
		(5.743)
LNVOLUME		0.158***
		(11.001)
PERCLTG		0.284***
		(4.946)
Year dummies	Included	Included
Industry dummies	Included	Included
Observations	123,650	123,650

TABLE 9

The Presence of LTG Forecasts on the Relation between Analysts' Forecast Errors and SUE

This table reports the regression results testing the effect of ex-ante presence of LTG forecasts on the relation between analysts' short-term forecast errors and SUE. See Table 2 for variable definitions. Models are estimated using ordinary least squares regression with standard errors clustered at the firm-level. t-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

	(4a)	(4b)	(4c)	(4d)
	FE1	FE1	FE2	FE2
Constant	0.003***	0.001***	0.002***	0.001**
	(10.368)	(2.674)	(9.575)	(2.183)
SUE	0.062***	0.053***	0.053***	0.048***
	(6.635)	(4.921)	(6.270)	(4.911)
DLTGISS		0.003***		0.003***
		(7.802)		(7.699)
SUE*DLTGISS		0.023		0.012
		(1.231)		(0.702)
Observations	175,865	175,865	175,865	175,865
R-squared	0.019	0.020	0.018	0.019

TABLE 10

The Presence of LTG Forecasts and SUE Persistence

This table reports the regression results testing the relationship between ex-ante presence of LTG forecasts and SUE persistence. See Table 2 for variable definitions. Models are estimated using ordinary least squares regression with standard errors clustered at the firm-level. t-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

	(5a)	(5b)	(5c)
	FPSUE	FPSUE	FPSUE
Constant	-0.004	0.001	0.021***
	(-1.041)	(0.259)	(4.482)
PSUE	0.384***	0.376***	0.387***
	(118.558)	(80.648)	(42.769)
DLTGISS		-0.008***	-0.012***
		(-5.485)	(-6.129)
PSUE*DLTGISS		0.015**	0.034***
		(2.555)	(4.495)
PSUE*PSIZE			-0.160***
			(-8.600)
PSUE*PDISP			0.021
			(1.625)
PSUE*PPRICE			0.020
			(1.054)
PSUE*PINST			0.043***
			(3.107)
PSUE*LOSS			-0.044***
			(-5.159)
PSUE*QTR4			-0.118***
			(-18.923)
PSUE*PEVOL			-0.072***
			(-5.784)
PSUE*DSTERESP			0.024***
			(3.204)
PSIZE			0.012***
			(3.253)
PDISP			-0.061***
			(-19.206)
PPRICE			0.002
			(0.601)
PINST			0.005*
			(1.709)
LOSS			-0.001
			(-0.478)
QTR4			-0.020***
			(-16.740)
PEVOL			0.053***
			(16.785)
DSTERESP			-0.008***
			(-3.945)
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	201,863	201,863	150,944
R-squared	0.154	0.154	0.160

TABLE 11

Tests of Market Efficiency for Firms With and Without LTG Forecasts

This table reports the regression results from nonlinear generalized least squares estimation of the stock price reaction to information in SUE. See Table 2 for variable definitions. The likelihood ratio statistic is distributed asymptotically as χ^2 with 1 degree of freedom. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

Panel A: Firms with and without LTG forecasts

	DLTGISS=1	DLTGISS=0
Parameter	Estimate	Estimate
α1	0.394***	0.378***
α1*	0.266***	-0.038
β1	0.131***	0.128***
Test of market efficiency:	α1 = α1*	α1 = α1*
Likelihood ratio statistic:	58.909	239.181
Marginal significance level:	0	0

Panel B: Full sample

Parameter	Estimate
α1	0.378***
α1*	-0.034
α3	0.016***
α3*	0.298***
β1	0.129***
(α1 - α1*) / α1	1.090
((α1 + α3) - (α1* + α3*)) / (α1 + α3)	0.329
Test of market efficiency:	α1 = α1*
Likelihood ratio statistic:	364.434
Marginal significance level:	0
Test of market efficiency:	α1 + α3 = α1* + α3*
Likelihood ratio statistic:	44.93
Marginal significance level:	0
Test of market efficiency:	(α1 - α1*) / α1 = ((α1 + α3) - (α1* + α3*)) / (α1 + α3)
Likelihood ratio statistic:	106.95
Marginal significance level:	0

TABLE 12

Controlling for the Determinants of LTG Forecasts

This table reports the regression results controlling for the determinants of LTG forecasts. See Table 2 for variable definitions. Panel A reports OLS regression results which incorporate determinants of the firm-level presence of LTG forecasts as control variables. Panel B reports OLS regression results which use the residual probability from the logit regression (RESIDUAL) in place of DLTGISS. t-statistics are reported in parentheses. ***, **, * indicate significantly different from zero at the 1%, 5%, 10% level, respectively.

Panel A: Including determinants of the presence of LTG forecasts as control variables

	(6a) ARQ
Constant	0.007
	(0.575)
PSUE	0.272***
	(8.110)
DLTGISS	-0.004**
	(-2.089)
PSUE*DLTGISS	-0.024***
	(-3.769)
Controls	Included
PSUE*Controls	Included
Year dummies	Included
Industry dummies	Included
Observations	150,447
R-squared	0.010

Panel B: Use residual probability of the presence of LTG forecasts (RESIDUAL) in place of DLTGISS

	(6b) ARQ
Constant	0.011***
	(3.916)
PSUE	0.029***
	(11.038)
RESIDUAL	-0.003
	(-1.629)
PSUE*RESIDUAL	-0.020***
	(-2.709)
Year dummies	Included
Industry dummies	Included
Observations	150,447
R-squared	0.004

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APPENDIX A: DETERMINANTS OF THE PRESENCE OF LTG FORECASTS

The issuance of LTG forecasts is not exogenous. Analysts make the decision of whether or not to issue LTG forecasts based on the costs and benefits of such actions. The decision is also subject to analysts' time and resource constraints. The determinants of the issuance of LTG forecasts may also be correlated with PEAD returns, causing correlated omitted variable problem which may bias my coefficient estimates. Thus, it is important that I control for these variables in my regressions. Based on the work of Jung, Shane and Yang (2008, 2012) and Zhang (2008), I discuss below some possible determinants of the issuance of LTG forecasts. As these determinants will be control variables in the PEAD tests, all variables are constructed at the firm level.

A.1. Costs-related determinants of LTG forecast issuance

The major cost for issuing LTG forecasts is the cost associated with collecting and interpreting long-term oriented information. Such cost is influenced by the information environment of firms, and is lower for firms with more abundant information from various sources and lower information uncertainty. Thus, analysts are more likely to issue LTG forecasts for these firms. I discuss ten variables that are expected to capture the information environment of firms: size, age, earnings volatility, financial health (Altman's Z-score), loss occurrence, M&A, restructuring, number of analysts who issue short-term forecasts for the firm, fourth quarter earnings announcements, and bad news.

Size (SIZE): Larger firms are expected to have a richer information environment and lower information uncertainty, and thus the cost of providing LTG forecasts for these firms is lower. In addition, from the benefit perspective, the demand for analyst services likely increases with firm size, since firms larger in size are expected to have a larger number of shareholders. However, size may also negatively affect the issuance of LTG forecasts. Larger firms likely have more complex corporate structures and business transactions; making it costly for analysts to interpret these information. Also, to the extent that larger firms disclose more information publicly, this could substitute analysts' forecasts and decrease the demand for LTG forecasts. Thus, the effect of SIZE on the issuance of LTG forecasts is ambiguous.

Age (AGE): Similar as size, older firms are expected to have a richer information environment and lower information uncertainty, leading to lower cost of providing LTG forecasts for these firms. However, older firms may have passed their growth stage and thus the long-term information demand for such firms may be lower. Thus, the effect of AGE is ambiguous.

Earnings volatility (EVOL): Higher earnings volatility indicates higher information uncertainty, and thus higher costs for analysts to interpret information and make forecasts. Therefore, it is less likely for analysts to issue LTG forecasts for these firms.

Financial health (ALTMANZ): Following Zhang (2008, 2012), I measure financial health using Altman's (1968) Z-score. Healthy firms likely have lower information uncertainty, and thus lower cost of collecting and interpreting information. Therefore, it is more likely for analysts to issue LTG forecasts for these firms.

Loss occurrence (LOSS): Firms occurring losses are more likely to be in financial distress. Information uncertainty is likely higher for these firms, resulting in higher cost of collecting and interpreting information. Also, negative earnings information is less relevant for firms' long-term earnings, as firms cannot keep losing money while remain solvent in the long-run. Thus, it is less likely for analysts to issue LTG forecasts for these firms.

M&A (MERGE) and *restructuring (SPECIAL)*: Firms that have recently been through an M&A or restructuring have higher information uncertainty, and thus information interpretation costs are likely higher for these firms. However, both M&A and restructuring are events that have long-term implications for firms, and the demand for long-term oriented information is likely higher after these events. Thus, the effects of MERGE and SPECIAL on the issuance of LTG forecasts are ambiguous.

Number of analysts who issue short-term forecasts (STENUM): Analysts' forecasts are important information sources. The information environment of a firm is likely richer and the average cost of information collection lower, when a large number of analysts follows the firm. Thus, analysts are more likely to issue LTG forecasts for these firms.

Fourth quarter earnings announcements (QTR4): Studies document that fourth quarter earnings announcements provide more information than do interim announcements (Cornell and Landsman, 1989). Thus, the information collection costs are likely lower for these earnings announcements, and analysts are more likely to issue LTG forecasts following these announcements.

Bad news (BNEWS): Negative earnings surprises likely associate with higher information uncertainty, and thus higher cost of information assessment. However, to the extent that managers manage expectations to avoid negative earnings surprises (Matsumoto, 2002), these surprises, if they do occur, may convey more information about a firm's fundamentals. In addition, the demand from investors for interpreting such information, as well as the demand from managers for further guiding investors' expectations, may be higher following these surprises. Thus, the effect of BNEWS on the issuance of LTG forecasts is ambiguous.

A.2. Benefits-related determinants of LTG forecast issuance

Benefits for issuing LTG forecasts come from investors' demand for long-term oriented information. This demand is likely higher when (1) a higher percentage of a firm's value depends on long-term earnings, or (2) a higher percentage of a firm's investors are long-term investors. I discuss three variables that are expected to capture the importance of long-term forecasting for a firm's valuation and the investment horizons of a firm's investors: book-to-market, R&D, and institutional ownership.

Book-to-market (BM): Firms with lower BM (growth firms) likely have a higher percentage of value depend on long-term earnings, and thus demand from investors for LTG forecasts is likely higher for these firms. However, information uncertainty is also likely higher for growth firms, leading to higher cost of information collection and interpretation for these firms. Actually, prior studies based on analysts' short-term forecasts document that growth firms have lower analyst coverage (Hong, Lim and Stein, 2000). Thus, I do not make a directional prediction on the effect of BM on the issuance of LTG forecasts.

R&D (RD): The benefits of R&D materialize in the long-term, and thus firms with higher R&D expenditures (as a percentage of market capitalization) likely have a higher percentage of value depend on long-term earnings. However, the outcomes of R&D are hard to predict, and firms with high R&D intensity likely have higher information uncertainty, leading to higher cost of information interpretation for these firms. Thus, the effect of RD on the issuance of LTG forecasts is ambiguous.

Institutional ownership (INST): Institutional investors are sophisticated investors who have longer investment horizons, and thus firms with higher institutional ownership are likely the ones with higher percentage of long-term investors. Therefore, it is more likely for analysts to issue LTG forecasts for these firms.

A.3. Constraint-related determinants of LTG forecast issuance

Constraints for issuing LTG forecasts come from the limited resource, time and intellect that analysts possess. I discuss six variables that are expected to capture the constraints that analysts face: analyst experience, number of firms that an analyst follows, analysts' issuance of cash flow forecasts, broker size, a firm's trading volume, and analysts' issuance of LTG forecasts for other firms.

Analyst experience (EXP): Analysts with more experience are likely more capable, and face less intellect constraint for issuing LTG forecasts. Also, experienced analysts can rely on their previous experience, and thus have lower marginal cost of issuing forecasts. Therefore, firms followed by experienced analysts are more likely to have LTG forecasts.

Number of firms followed by analysts (NUMFIRM): Given the time constraint that analysts face (i.e., a person can at most work 24 hours a day), analysts who follow a large number of firms are less likely to have additional time to engage in optional forecast activities, e.g., LTG forecasts. Thus, firms with analysts who follow a large number of firms are less likely to have LTG forecasts.

Analysts' issuance of cash flow forecasts (DCFISS): Similar as LTG forecasts, analysts' cash flow forecasts are another example of optional forecasts. Analysts who issue cash flow forecasts likely face less time/intellect constraint, and thus these analysts are more likely to issue LTG forecasts. However, given the time constraint, analysts who spend time on cash flow forecasts may have less time to spend on LTG forecasts. Thus, the effect of DCFISS on the issuance of LTG forecasts is ambiguous.

Broker size (BSIZE): Large brokerage firms have more resources (e.g., research support, management connections), and analysts who work for these firms likely face less resource constraint. Thus, firms with analysts from large brokerage firms are likely to have LTG forecasts.

Trading volume (VOLUME): Studies document that trading volume is a proxy for brokerage commissions (Alford and Berger, 1999). Stocks with high trading volume likely generate more brokerage commissions, and thus brokerage firms are likely to allocate more resources to these stocks. Therefore, it is more likely for analysts to issue LTG forecasts for these firms.

Analysts' issuance of LTG forecasts for other firms (PERCLTG): Analysts who are more likely to issue LTG forecasts for other firms likely face less resource, time and intellect restraints for issuing LTG forecasts. Thus, firms with analysts who are more likely to issue LTG forecasts for other firms are likely to have LTG forecasts.